Literature Review on Forest Fire Detection for Real-time Monitoring Using Unmanned Aerial Vehicles

By: Chi Yuan

Supervisor: Professor Youmin Zhang

Department of Mechanical and Industrial Engineering

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Abstract

Forest fires are a universal problem that both confronts and confounds many countries. Such fires not only destroy large amount of natural resources, but also destroy wildlife and their natural habitat, wreaks general havoc on ecosystems and creates environmental pollution. For all that, fire fighting is one of today's most important matters for natural and environmental resources protection and preservation. The growing concern regarding environmental devastation of this kind is the underlying reason for the development of modern fire-detection system. UAVs (Unmanned Aerial Vehicles) with computer-vision based systems provide rapid and low-cost approaches to meet the critical requirements of spatial, spectral, temporal resolutions and have more potential for forest management than conventional satellite imagery, manned vehicle and ground measuring equipment.

In this literature review, the key issues of current researches in the field of forest fire detection using UAVs are presented. Several forest fire detection systems using UAVs are listed in the second section. A general description of the forest fire detection using UAVs system is presented before the main section of review.

UAVs application in forest fires detection has attracted researchers' attention worldwide. A large number of papers referred to forest fire detection methods and algorithms (not only based on UAVs, but also manned vehicle and ground measuring equipment) are reviewed in this report. Some challenging issues are also addressed for further research, like separation of noise origin from the fire origin, low false alarm rate, adapt to changes in environment conditions, fusion of infrared, visual images and other sensors and the elimination of image vibration caused by turbulence, unavoidable control errors and the UAV itself to give an overview of the development and future work in this area.

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1. Introduction

Forests purify water, stabilize soil, cycle nutrients, moderate climate and store carbon. They create habitat for wildlife and nurture environments rich in biological diversity. They sustain forest products industry that supports hundreds of thousands of jobs and contributes billions of dollars to the country's economic wealth. However, hundreds of millions of hectares are unfortunately devastated by forest fires each year [1].

Forest fires are universal problems both confronts and confounds many countries since they have disastrous social, economic and environmental impacts. Forest fires not only result in the devastation of forests and the wildlife that inhabits them but also result in damage to public safety, economic wealth and create environmental pollution [2]. Forest fires represent a constant threat to ecological systems, infrastructure and human lives thus forest fires fighting is considered as one of today's most significant events for natural and environmental resource protection and preservation [2,3].

Early detection and suppression of fires deem crucial for fighting fires, so forest fire perception in real-time is a pivotal part for the development of advanced fighting strategies [1]. Traditional fire protection methods use mechanical devices or humans to monitor the surroundings which are very dangerous activities requiring extensive human resources [4]. However, due to rapid growth of the electronics, computer science and digital camera technologies, artificial vision and image processing techniques have been developed mainly for forest fire detection and computer-vision-based systems play a very promising role to effectively replace conventional forest fire detection systems [4, 5, 6].

The current research to forest fire detection can be divided into three different groups: ground systems, systems on aerial means, and satellite based systems [7]. However, these platforms still have different technological and practical problems for their use in operational conditions. Ground-based measurement equipment is limited in the range of surveillance. Satellites systems are generally not considered accurate enough for capturing detailed data necessary for forest fire detection since the temporal resolution, time scale and spatial resolution of satellite systems is still very low to meet the requirements [8, 9]. Manned aerial vehicles are typically large and expensive. In addition, hazardous environments and operator fatigue can potentially threaten the life of the pilot [7].

Therefore, UAVs (Unmanned Aerial Vehicles) with computer-vision based systems represent a natural and good option to fill in this gap by providing rapid and low-cost approaches for meeting the critical requirements of spatial, spectral, temporal resolutions and have more potential for forest management than conventional satellite imagery, manned vehicle and ground measuring equipment [7,12,13,14]. UAVs allow to a rapid and low-cost response to forest fires and accomplish long missions which are way beyond human capabilities. They also allow execute redundant and monotonous tasks such as systematically monitor large territories and measuring and monitoring risk, uncertainty and inventory in a forest simultaneously. They are lighter, much simpler to repair and require less management and operation staff [8, 15-18]. For that all, UAVs application in forest fires detection has attracted researchers' attention worldwide.

2. Brief Review on Development of the Forest Fire Monitoring System Based on UAVs

Several decades of forestry research have resulted in many advances in the field of forest fires monitoring. The Fire Weather Index (FWI) system being developed by the Canadian Forest Service and the National Fire Danger Rating System (NFDRS) introduced by the National Oceanic and Atmospheric Administration are two examples of such advances. But until now, very few papers have been identified considering forest fire monitoring using multiple UAVs around the world. A review of several forest fire monitoring systems using UAV are listed below.

In the work of Casbeer et al. [27], the feasibility of the application of a team of small (low altitude, short endurance) UAVs to cooperatively monitor and track the propagation of large forest fires is explored. The paper provides simulations using a numerical propagation model for the forest fire monitoring and detection. However, results in actual fire fighting activities have still not been carried out [30].

The Airborne Wildfire Intelligence System (AWIS) includes wildfire detection and mapping of the fire-front and burned area [25]. In Alberta, AWIS has been used for wildfire hotspot detection, fire front and burned area perimeter mapping, research into the effects of fire and its severity, and to document burn patterns across the landscape.

In addition, in [28] a method for the ortho-rectification of images gathered from a UAS

(Unmanned Aerospace Surveillance), and their application in fire monitoring activities is presented. However, no actual fire monitoring results are described.

The use of small and simple fixed-wing UAVs for forest fire detection and fighting is being analyzed by the UAVNet European Network [38]. In the FiRE project [23], fire detection and localization was demonstrated by an ALTUS UAS and an adaptation of the Predator UAS.

While the FiRE project considers forest fire detection and monitoring tasks by a single and complex UAV with complex sensors, the COMETS European project addressed the use of a team of simpler UAVs. In the COMETS project, instead of using a single powerful UAV with significant on-board resources but also with high cost, the application of a fleet of lower cost UAVs for forest fire fighting is proposed. These UAVs can be used as local flying sensors providing images and data at short distance. This project presented experimental results of multi-UAV forest surveillance, forest fire detection, localization and confirmation as well as fire observation and measurement obtained in the COMETS project. Although there is still the need of further research and development, the results represent a significant step towards the application of UAVs in forest fire operational conditions [24].

WITAS UAV project is a long term basic research project located at Linkoping University (LIU), Sweden [39]. This project focuses using active vision system consisting of digital video and IR cameras as the main sensory components and a fleet of UAVs to real time monitor and detect forest fire.

Despite the mentioned large variety of forest fire detection systems give a possibility to detect the forest fire, the number of automatic forest-fire monitoring and measuring systems is still scarce and the false alarm rate is not very low. Further investigation on this topic remains an important issue.

3. General Description of the Forest Fire Monitoring System Based on UAVs

For a fire detection mission, the UAV fleet is endowed with a task consisting of patrolling an area. The task planner takes into account the characteristics of the UAV (payload and time of flight) and the onboard sensors (field of view) to compute the paths to be assigned to each one. Then, the autonomous detection relies on the ability of the system to detect the fire in the images provided by the UAVs and to localize the alarm. The main objective is to automatically monitor and detect forest fires in real time, such as the location and shape of the fire front, the rate of spread and the fire flame height [32].

3.1 Forest Fire Monitoring Based on UAVs System Description

Forest Fire Monitoring System is composed of a team of aerial vehicles (with different kinds of sensors) and a ground central station, Figure 1 illustrates such a system.

1) Vehicles and sensors: The UAVs are equipped with differential GPS receivers and Inertial Measurement Units (IMUs) which allow them to localize themselves in a common world reference frame. They should carry infrared and/or visual cameras as well as pan and tilt units for perception purposes. Moreover, all of the cameras in the system are calibrated before the flights by using artificial patterns. All the images gathered are tagged locally with the composed pose and orientation of the UAV and the pan and tilt unit, timestamps and calibration information. The UAVs carry onboard communication devices to be able to receive commands from a ground station, and to send information back to it [32].

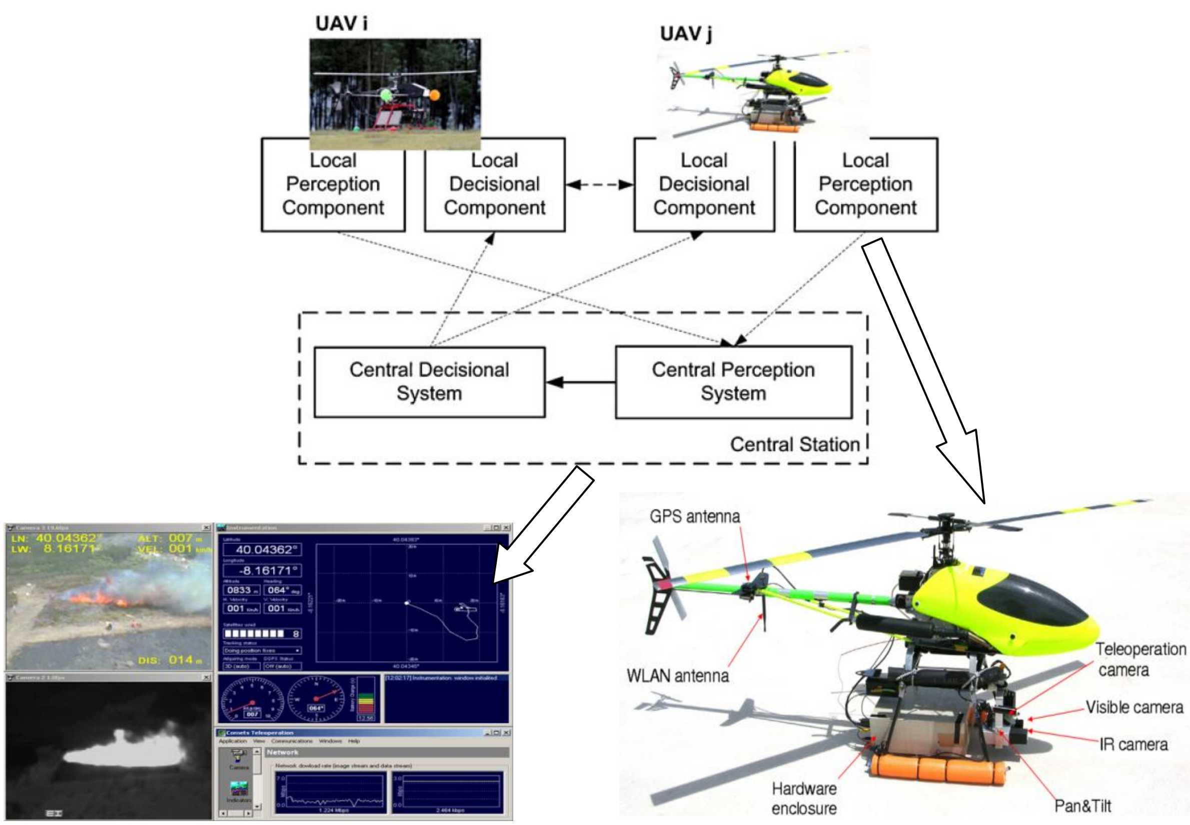

Figure 1: The system consists of several vehicles (with sensors of differential GPS receivers, Inertial Measurement Units (IMUs), infrared and visual cameras etc.) and ground central station [32].

2) Decision-making system: The system requires that the UAVs are able to autonomously navigate between waypoints, the coordination and control of the fleet of aerial autonomous vehicles of

the system [33, 34].

3) Perception system description: This system considers all the information gathered (images and videos) and provide features related to the fire and smoke by UAVs to monitor the fire and estimate the evolution of the fire [32].

3.2 General Description of the Forest Fire Monitoring Approaches

After reviewing the former papers, forest fire monitoring mission can be generally decomposed into the following three stages: fire search, fire confirmation and fire observation.

3.2.1 Fire search

In this stage, all the UAVs with fire detection capabilities are used to patrol the area to be surveyed. The ground control centre divides the area among the UAVs attending to the characteristics of the terrain and the capabilities of each UAVs and their sensors on-board. The control centre also determines the path for each UAV.

Each UAV patrols its surveillance region searching for potential fires. Both UAVs apply the fire segmentation methods to identify automatically fire alarms by using their fire sensors including visual cameras and infrared cameras.

3.2.2 Fire confirmation

If one (or several) fire alarm is detected, fire search stage finishes and then the fire confirmation stage starts. The control centre makes new plans and the UAV that detected the fire is commanded to hover at a safety distance from the fire alarm. Other UAVs are sent to confirm the alarm by using their sensors. If the alarm is found to be false, then the fire search stage is resumed. If the alarm is confirmed as a fire, then the fire observation stage starts.

3.2.3 Fire observation

If the alarm is confirmed to be true, the tasks for the UAVs are re-planned. The UAVs are commanded to obtain information of the fire alarm. Thus, they synchronously obtain images of the fire from different points of view. The images are stabilized in real time [16].

3.3 Basic Methods for Automatic Forest Fire Perception Functions

As described in [85], the main image processing techniques implemented for automatic fire detection and monitoring can be briefly presented as below.

3.3.1 Fire segmentation

Fire segmentation is essential for fire detection. The main objective is to differentiate fire pixels from background pixels. Two segmentation techniques are commonly applied depending on the type of image: visual or infrared (Figure 2 shows visual and infrared images taken by an UAV and its corresponding segmented images).

Automatic detection of fires by using images from infrared cameras requires the consideration of the camera's characteristics. Thus, in thermal cameras, the difference between fire and non-fire temperatures allows to establish suitable temperature threshold values to distinguish fire from background. The infrared camera installed onboard the UAV provides images in which the radiation intensity is represented by grey levels. In this case the image segmentation required for fire detection is typically based on image thresholding. The thresholding technique should consider the particularities of the application such as blurring in the image induced by high-frequency vibrations of the engine [16]. Automatic detection of fires by using images from visual cameras, three characteristic features of fire: color, motion, and geometry were widely used in image segmentation which can be referred in [85].

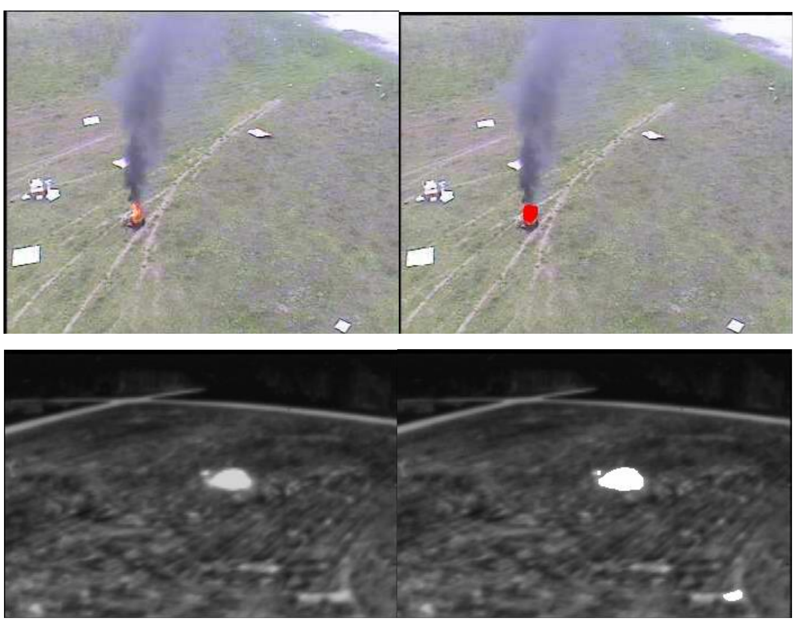

Figure 2: Segmentation of visual and infrared images: original (left) and segmented (right) images [16].

3.3.2 Automatic geo-location

The automatic geo-location method is based on projecting the image on a terrain map. If the camera is calibrated and a digital elevation map is available, it is possible to obtain the geo-referenced location of an object in the common global coordinate frame from its position on the image plane. It is also possible to compute the errors of the object localization by considering the terrain map and the errors in the position and orientation of the cameras. The determination of the geo-referenced location of the objects observed on the images is required for many applications. The location of the UAV system is known through GPS measures. The orientation of the cameras is computed by composing the orientation angles of the pan & tilt system with the orientation angles of the body of the UAV, which are estimated with IMU unit and compass.

3.3.3 Other techniques

A wide variety of other image processing techniques such as data fusion should be implemented for cooperative fire detection and image stabilization. Automatic fire detection is a difficult task. In forest scenarios it is easy to find many false alarms originated by many solar reflections, heated objects, human activities and others [46]. Fusion of data from different sources has been applied for false alarm reduction in many applications, and also for forest fire detection [6]. It integrates information from the fire sensor, from visual cameras and from the infrared camera [48].

Many applications also require having motion-free sequences of images. The approach adopted for image stabilization obtains the apparent image motion by means of a robust interest point matching algorithm, and compensates the motion by warping the images to a common image frame [35, 36].

4. Review on Image Processing Techniques in Forest Fire Detection

Fire detection estimations are mainly obtained from the processing of both infrared and visual images. In order to decrease fire damage, appropriate early fire detection techniques and using the navigation sensors onboard the UAV to compute position of the alarm has attracted increased attention [53]. A series of papers have focused on fire fighting and prevention. Most of the early researches detected fire by videos, like [49, 61-63, 68-69, 74]. Later on, researchers gradually use visual cameras to do detection in the real situation. Recently, more and more researchers and research teams around the world use visual and infrared camera to detect fire separately or combined by the images fusion.

4.1 Processing of Visual Images

Vision-based systems generally make use of three characteristic features of fire: color, motion, and geometry. Over the last decade image processing technique has been widely used with different segmentation methods. Many segmentation algorithms based on various approaches have been developed for forest fire. Most of these methods use the discriminative properties in color spaces to obtain fire regions in the image. Generally, models are obtained in specified color spaces to represent fire zones in the image; thresholding is a common technique used to segment the fire regions based on such models [53]. Especially, the color and motion information is usually used as a pre-processing step in the detection of possible fire or smoke. A list of publications in this area is summarized in Table 1.

Table 1: Visual image processing approaches classification by characteristic features of fire.

Used Features	**Approaches**	**References**
Color	Training-based algorithm	[16, 29]
	Statistic and binaryzation	[58]
	Fuzzy logic	[56]
Motion	Accumulative motion model	[64]
	Neural network	[60]
Color and motion	Genetic algorithm	[50, 52]
	Computer-vision	[72]
	Wavelet analysis and training-based algorithm	[51]
	Training-based algorithm	[49]
	Fourier Transform	[67]
	Bayes and fuzzy C-Means	[66]
	Adaptable Updating Target Extraction Algorithm	[70, 71]
	Distributed neural network	[26, 31]
	Fuzzy-neural network	[37]
	Fuzzy Finite Automata	[19]
Geometry	Fuzzy logic, artificial intelligence	[59]
Color, motion and geometry	Fuzzy logic	[65]

In order to decrease the cost of devices and personnel in practical experiment and save the experimental time. Many researches and algorithms are tested by the forest fire videos. Chen et al. used color and motion features to extract real fire and smoke in video sequences [49]. Töreyin et al. [51] proposed a real-time algorithm which combined motion and color clues with fire flicker analysis on wavelet domain to detect fire in video sequences. Töreyin et al. [50] combined 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 on they have employed the same fire detection strategy to detect possible smoke samples which is used as early alarm for fire detection [52]. They combined color information with shape analysis to detect possible smoke samples where false alarm rate is decreased using a flicker analysis of smoke region. In [67], Jin and Zhang proposed a novel method to detect fire and flame by processing the video data captured by an ordinary camera monitoring an open scene by combining fire flicker and color clues to reach a final decision.

Although most of the previous researches are just focused on the detection of forest fire by fire, in order to detect early forest fire or more precisely, the smoke is an important feature for early fire detection. A series of research papers have focused on smoke detection, smoke segmentation and smoke alarm devices. In [55], Chen et al. continued their former work in [49] and proposed a chromaticity-based static decision rule as well as a diffusion-based dynamic characteristic decision rule for smoke pixel judgment. Experimental results show that this method can provide an authentic and cost-effective solution for smoke detection. But it is based on video processing. In [60], back propagation neural network is used for the discriminating model. Experiments show that the proposed method can distinguish between smoke videos and non-smoke videos with quick fire alarm and low false alarm rate. In Yuan [64], a smoke detector is proposed which uses an accumulative motion model based on the integral image by quickly estimating the motion orientation of smoke. The estimation does not have high accuracy and will affect the decision; therefore the author has used accumulation of the orientation over time to decrease this effect. Experimental results show that the proposed method demonstrates good robustness for smoke detection. An approach to detect the fire smoke in real-time alarm systems is proposed in [65]. Experimental results show that the fire smoke can be successfully detected under various area conditions. Though the results obtained are promising, it is still necessary a significant research and development effort to obtain a system suitable to be implemented in operational conditions.

Although each individual forest fire or smoke detection method has been summarized in Table 1, there are only few experiments like [16, 29, 58, 72] carried out in the practical situation by detecting fire. Most of these researches are conducted by a research team from University of Seville (in Spain) which is part of COMETS project. They used UAVs based on color information to do many experiments in the practical situation.

In recent years, researchers focused on fire detection by using intelligent methods to reduce the false alarms rate and the cost of sensors. As can be seen in Table 1, the algorithms used in most of the researches [19, 26, 31, 37, 56, 59, 66, 70, 71] are artificial neural networks, fuzzy logic, expert system, and fuzzy neural networks. Experimental results show that the proposed approaches efficiently detect forest fires. But they haven't been applied on UAVs to monitor and detect forest fire. Applications in real systems using UAVs are still scarce and existed applications produced high false alarm rate and image vibration issues which is still a big challenge and needs further research.

4.2 Processing of Infrared Images

As infrared images are not affected by smoke (which is transparent at these wave lengths), it is possible to employ negative information from the contours (that is, if nothing is obtained on the image plane it is very likely that there is no fire), which is not the case of visual images.

The aim of the processing of infrared images is to produce binary images containing fire alarms while discarding false alarms. The processing of infrared images consist in computing a threshold value since fires appear in infrared images as high intensity regions, and applying some heuristic rules to discriminate false alarms. The threshold selection method should take into account the particular conditions of the application to discard false alarms. Although the temperature of fire (often over 900ºC) is much higher than the temperature of the image background, temperature based criteria cannot be used for thresholding since the measures of temperature are influenced by the emissivity indices of the materials, which are very difficult to estimate in such an unstructured environment.

In view of fire detection by infrared image processing, only few research work have conducted in the past. In [20], Martinez-de Dios and Ollero described a training-based threshold selection method. Later on, Martínez-de Dios et al. [21] adapted the method in [20] to the application which was carried out by selecting training infrared images with different illumination conditions, different image backgrounds and different objects including fires and false alarms. A set of thermocouples are used to detect the location of the fire front in [40]. The work in [41] describes a method based on linear transformations of infrared images to compute the positions and the rate of spread of a linear fire front propagating on a flat surface. The processing of multispectral infrared images to determine the fire perimeter, the 'active' fire line and the fire propagation direction is proposed in [42]. In [6], Arrue et al. applied fuzzy logic algorithm and Artificial Neural Networks (ANNs) in infrared-image processing. A multiple ANNs model for an infrared (IR) flame detection system is proposed by Huseynov et al. [77]. The experimental results compared with expert system demonstrate that the proposed method can detect noise faster than expert system.

A problem of the processing of images from miniaturized infrared cameras is that in the current state of technology these cameras have low sensitivity. Thus, they require high detector exposure periods to generate the images, but the high frequency vibrations of the UAVs often originate blurs in the images which is a challenge for current researches. So, these particularities should be considered in the thresholding method used.

4.3 Fusion of Both Visual Images and Infrared Images

Generally, there are many approaches for reducing false alarms and improving fire detections. A very important method is the fusion of information of different natures, at different levels of abstraction using intelligent methods or combination of other techniques such as probability or statistics.

As example, the system described in [44] combines infrared and visual cameras to obtain fire measurements in laboratory experiments. This work was developed and validated in laboratory fires in controlled conditions. But the extension to forest fires is not addressed in these papers. A forest fire perception technique which computes a 3D perception model of the fire and could also be used for visualizing the fire evolution in remote computer systems is presented by Martinez-de Dios et al. in [73]. The main results of this method is the robustness of the system against the potential sources of errors which can be performed by using complementary information, supplied by several cameras types (visual and infrared) at different positions. In [75], da Penha Jr and Nakamura proposed and evaluated two algorithms, based on information fusion methods, for fire detection in rainforests where they only had light and temperature sensors. Experimental results indicate that forest fire can be detected at night by just using light measurements. In addition, light data can be used to distinguish heat resulting from sunbeam and fire. An adaptive fusion method for fire detection is presented in Luo et al. [76]. They use three sensors for fire detection such as smoke sensor, flame sensor and temperature sensor and they use neural network in fusion center structure. Later on, they continued their former work to use a smoke sensor, flame sensor, and temperature sensor to detect fire incident [10]. In [11], Yao et al. present an adaptive resonance theory model and the three-layer back propagation neural network for two-layer fusion processing for temperature, smoke and carbon monoxide sensors information. In [22], multi-sensor data fusion technology is used in fire detection, which can resolve existing problems in traditional fire detection, such as lower-grade intelligence, high mis-warning rate, delay-warning etc. According to the fire signal's inherent character, a 3-layer data fusion structure is used and the data are fused by the fuzzy inference system to get the final fire probability.

Although many algorithms and approaches on image information fusion have been addressed in the previous researches, how to optimize the number of features that are used in fire detection as well as false alarms in alarm devices and equipment is still a challenge for current research which can reduce the burden of calculation of onboard computer, decrease the cost of sensors and other equipment, and improve the false alarm rate.

4.4 Propagation Prediction

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Dynamics of forest-fires are considered as one of the most important scientific challenges in the field of the environmental studies [47]. Predicting behavior of fire propagation can help the fire fighters. In order to estimate the evolution of the fire front, the first issue is to devise a convenient representation of the information related to the fire. Rate of Spread (ROS) is one of the most significant parameters in the description of forest fire behavior, since it is directly related to fire intensity [54] and flame front geometry [84] and, thus, to the levels of danger associated with its propagation.

During recent years, new techniques have appeared based on discrete or continuous fire monitoring by image acquisition with either IR or video cameras. All of researches in this field used many intelligent algorithms, like: (1) genetic algorithms, (2) expert, knowledge and rule based systems, (3) artificial neural networks. These techniques are becoming widespread in the field of forest fires due to their high precision and versatility with regard to experimental scenarios.

As in [41], a method for the fast and accurate calculation of the ROS by processing infrared images was presented. This method is easily applicable to other experimental scenarios that are more complex than these described in this paper, such as prescribed burnings or real forest fire emergencies. A Cellular Automaton (CA) that predicts the spread of forest fire is proposed in [78] which also use cellular automata, genetic algorithms and dedicated processors for modeling and simulation of locally interacting systems and physical processes. Improving forest fire spread prediction is possible by using a dynamic data driven Genetic Algorithm (GA) [79]. INCEND-IA is a Knowledge Base System (KBS) for prediction and decision support in fighting against forest fires [80]. Their proposed system was used in some areas in Spain. An enhanced prediction scheme is described in Abdalhaq et al. [81] which use recent fire history and optimization techniques to predict near future propagation. In Fowler et al. [82] the suitability of a fuzzy rule based system is based on the ability of solving the forest fire size prediction problem. The formalized approach proposed for input parameter optimization for real-time disaster modeling using the example of forest fire spread prediction is presented in Wendt et al. [83]. In [57], Li et al. addresses a fuzzy segmentation algorithm to map fire extent, active fire front, hot burn scar and smoke regions based on a statistical model.

4.5 Localization\Geo-location of the Fire

For efficient fire fighting, the personnel on the ground need tools that can predict fire front position. This is possible with information like the current state and the dynamic evolution of fires. GPS systems make it possible to know the current position of the resources and satellite images can be used to track fire. However, the time scale and spatial resolution of these systems are still insufficient for the needs of operational forest fire fighting and cost is too high. Multisensory fusion which is conducted using vision sensors and GPS can meet this requirement.

The method described in [45] uses stereo-vision units with visual cameras to obtain fire geometry measurements. It is useful in laboratory fires but does not address practical problems of real forest fires. In [28], Zhou et al. present a method for ortho-rectification of images gathered from a UAV, for their application in fire monitoring activities. They discuss specific problems that have to be solved in the case of forest areas, and present very preliminary results on aerial images gathered from a conventional aircraft. However, no actual fire monitoring results are presented. In [55], Tipsuwanpom et al. consider the effectiveness of image processing by using artificial neural network to detect fire by using a camera.

The experimental results show that this method could detect the location of a fire from the image.

4.6 Eliminating Image Vibrations

Considering UAVs with hovering capabilities, unavoidable control errors, turbulences and vibrations produce changes in the camera position, which leads to image motion. This motion can affect to the previously described algorithms and therefore, it is necessary to cancel it. Electro-mechanic systems can be used to eliminate vibrations, but these systems are usually heavy, expensive and have a residual vibration as stated in [32].

To overcome this problem, a simple and cheap approach can be used for software-based image motion estimation and cancellation which is image processing procedure. This can be achieved if the apparent motion between consecutive images is computed. The existing researches are scarce in this area, and [32, 35, 36] are the only very few papers mentioned this method. So image vibration elimination is also a potential and practical research topic.

5. Conclusion and Future Works

Many techniques have been applied to fire fighting. However, the vast majority of existed techniques still have different practical problems for their use in operational conditions, such as low reliability, high costs and etc. Using UAVs carried with computer-vision based systems to detect forest fire can provide rapid and low-cost approaches to meet the critical requirements of forest fire fighting, as they can cover the gap between the spatial scales given by systems based on satellites and those based on cameras on towers. Moreover, UAVs can adapt their deployment to avoid the inconveniences of other approaches, like the presence of smoke, or to cover the more convenient places. Meanwhile, they have been already demonstrated their possibility of fire detection, localization and observation in the previous limited number of research papers.

Since forest fires are highly complex, non-structured environments, where the use of multiple sources of information at different locations is essential. In addition, fire evolution is very difficult to be predicted, the presence of smoke may occlude the images, mimic flame features of sunlight, moonlight, vegetation or animals may cause false alarm or alarm failure. Some issues should be deeper investigated and further researched. One of them is the scalability of the proposed approaches. In order to apply the techniques in practical situations, UAVs with higher endurance are also required.

Moreover, in automatic fire detection the separation of noise origin from the fire origin is still a significant issue.

In addition to the issues mentioned above, a problem of processing images from miniaturized infrared cameras is that these cameras have low sensitivity with the current state of technology which will lead to alarm failure, thus higher detector exposure periods are needed to generate the images. These particularities should be considered in the thresholding method used. Whereas the high frequency vibrations of the UAVs often result in blurs in the images which may cause the failure in image capture. So the elimination of image vibration worth more research work since it is vital in acquiring clear and stable images for further processing.

Historically, very simple conceptual procedures have been used to experimentally determine the ROS and it is one of the most significant parameters in the description of forest fire behavior. To develop a simple and very practical method for computing the ROS of a flame front from a sequence of images recorded by an IR camera can be one of future work.

Existing researches showed that the combination of infrared and visual images is very useful to provide robust fire detection with high detection probability, low false alarm rate and the capability to adapt to changes in environment conditions. So, this is also worth deeper investigation. Meanwhile, how to optimize the number of features in image information fusion that are used in fire detection as well as false alarms in alarm devices and equipment is also a challenge for current research.

Finally, it is worth mentioning that another related research topic concerns using vision sensors and GPS to localize the location of fire is a complicated technology and few previous researches in forest fire monitoring referred to this.

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