Design and Research of Forest Farm Fire Drone Monitoring System Based on Deep Learning

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Abstract. In this work, we present a forest fire monitoring system using drones and deep learning. The proposed technique aims to solve the problems of traditional forest fire monitoring techniques, such as blind spots, poor real-time performance, expensive operational costs, and large resource consumption. We use image processing techniques to determine if the frame re-turned by the drone contains fire. This process is accomplished in real time and the resultant information is used to decide if any rescue operation is needed. The method proposed in this work has simple operations, high operating efficiency, and low operating costs. In addition, the proposed technique provides digital ability to monitor the forest fires in real-time effectively. Thus, it can assist in avoiding disasters and greatly reduce labor costs and other costs for forest fire disaster prevention and suppression.

Keywords: Deep learning algorithm · Drone · Forest farm · Fire insurance

1 Introduction

With the rapid development of society, people have put forward new requirements for the ecological environment. Fire hazard, as one of the eight natural disasters, has the characteristics of fast spreading, difficult to control, and strong destructiveness. Therefore, after fire hazard, it often severely damages the ecological environment and threatens the safety of property and life.

At present, the existing forest fire monitoring methods include artificial patrol, observation tower and satellite remote sensing, etc., each of which has its own advantages and disadvantages. Artificial patrolling can go deep into the forest to check the blind areas that are difficult to observe. It has strong mobility and can selectively select key patrolling routes, but the efficiency is low, the field of view is narrow, and it is greatly affected by the topography and landform; The observation tower has a wide field of view and can observe a large area of forest with the help of telescopes and other equipment. However, in the densely wooded areas, there are blind areas of vision and poor mobility

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and the observation range depends on the position of the observation tower; Satellite remote sensing has the broadest detection area, can accurately locate, and conduct all-weather observations, but the cost is high and can only be identified when a large fire area is formed. As a product of the rapid development of science and technology, drone technology has the advantages of fast flying speed, easy control and strong real-time performance. Therefore, it play an important role in promoting and has been widely applied in forest fire prevention and detection, fire behavior and rescue monitoring of forest fire prevention.

The proposed deep learning-based forest fire monitoring system comprises a drone and a remote monitoring system terminal. The proposed forest fire disaster monitoring introduces the drone platform in the forest fire prevention system, which has the capability to provide early warnings on the basis of video fire detection technology [1]. The work flow of the forest fire monitoring system based on deep learning and drone technology consists of multiple steps. First, the drone is equipped with a high-definition camera and performs the flight operation according to the preset patrol route to ensure that it covers the entire area under observation in such a way that there are no blind spots [2]. And the drone's position is determined by GPS in real time [3]. Second, the drone transmits the collected video and image information to the ground remote monitoring software in real time [4]. Third, this monitoring system makes use of forest fire deep learning algorithm to analyze and determine whether there is a fire disaster. When a fire incident occurs, the system triggers the alarm [5], and the user observes the dynamic information of the forest fire on the monitored host computer interface in real time [6]. This information is dispatched to the relevant person to take fire preventive measures [7]. Figure 1 presents the flowchart of the proposed system.

2 Overall System Design

2.1 System Hardware Design

1) **UAV system design**

   The UAV forest fire monitoring system comprises a GPS module, an image acquisition and transmission module, a communication module, and a flight control module [8]. These UAV components accomplish various tasks, such as the UAV flight control, autonomous landing, GPS based positioning, image acquisition and transmission [9].

   In this work, we select CUIM600 drone for the implementation of forest fire monitoring system. This drone adopts a modular design similar to M100, which is convenient to use and easy to install. The CUIM600 drone is also equipped with an efficient power system, integrated with dustproof, autonomous cooling in addition to other functionalities. The drone has the capability to carry items up to 6.0 kg and flies for 30 min with no load attached. In addition, the drone has a maximum flight speed of 18 m/s (ignoring wind conditions). The professional-level A3 flight control system and the sine drive technology application for intelligent ESCs also assist significantly in improving the reliability of flight performance [10]. In order to suppress the impact of the drone flight on the image captured during the drone flight, the proposed system uses the DJI Zenz Z3 gimbal camera. This is a three-axis

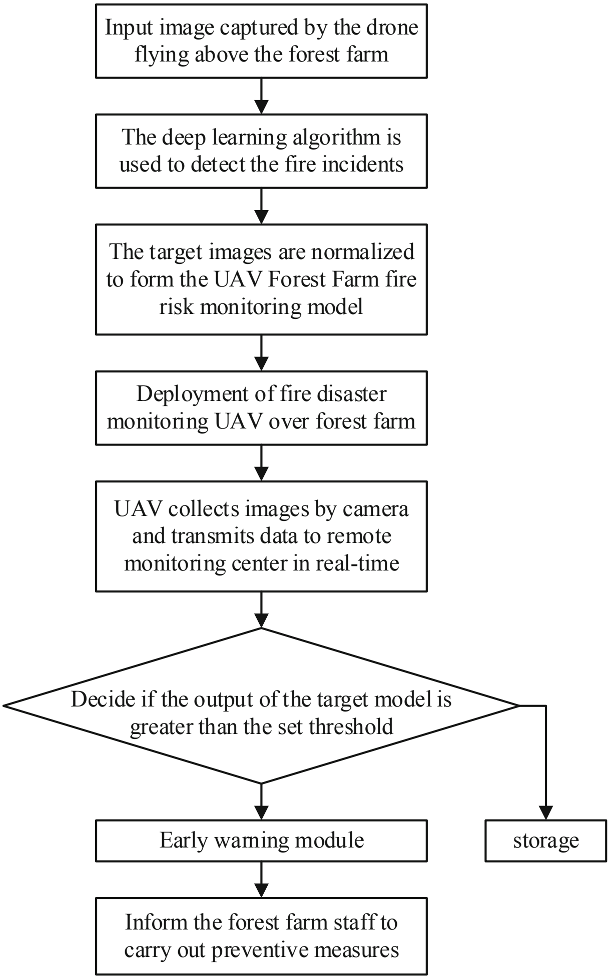

Fig. 1. The flowchart of the proposed deep learning-based forest fire monitoring system.

stabilizing gimbal camera. This camera has the ability to efficiently compensate for the jitters caused during the image acquisition process [11], when the drone moves forward, backward or when the flight altitude changes, thus, ensuring the good quality of the acquired images. Moreover, the cam-era also supports 3.5× optical zoom and 2× digital zoom, and also supports 4K Ultra HD video recording at 30 fps.

2) **Design of remote terminal monitoring system**
The remote monitoring system is used for receiving, processing and storing the data acquired by the drone. In addition, the ground center also provides the functionalities of deep learning-based fire detection and alarm triggering [12]. The staff have the ability to observe the acquired forest images in real-time on the ground monitoring terminal. When a fire incident occurs, the ground center provides real-time

dynamic information. The ground center's hardware equipment includes a PC and a communication module for receiving image information and other data, such as drone location, etc. [13].

3) **Hardware aspects of image acquisition**
The signal obtained from the video source is transmitted to the image acquisition card through the video interface. The signal first undergoes A/D conversion, and is then decoded by a digital decoder. The resultant is then compressed into a digital video, and is transmitted to the PC [14]. The frame grabber collects the image frames continuously from the input video, and transfers the data to the PC before acquiring the next image frame [15]. Therefore, the key to achieve real-time acquisition is highly dependent on the time taken to process each frame. If the time required to process a frame exceeds the interval between two adjacent frames, the image data is lost, i.e., the phenomenon of frame loss occurs. The video acquisition and compression operations of the image acquisition card are implemented together [16].

2.2 System Software Design

The software part of this system consists of unmanned aerial vehicle control system, data processing and communication system, and remote upper computer management system. This setup is presented in Fig. 2.

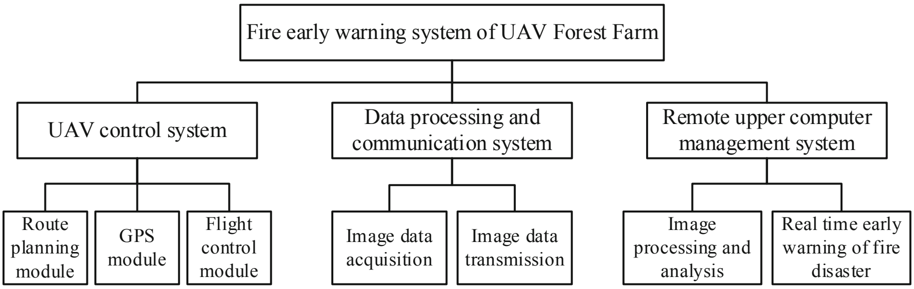

Fig. 2. System software composition design.

1) **UAV control system**
The drone control system is used to control the drone flight and flight information feedback from the drone, including information from route planning module, GPS module, and flight control module [17].

2) **Data processing and communication system**
The data processing and communication system is used to transmit the data and process the received forest images. In addition, this software is also responsible for managing the acquired data, including fault information, information regarding fire incidents and disasters, drone flight status information, and user login information. The data processing flowchart is presented in Fig. 3.

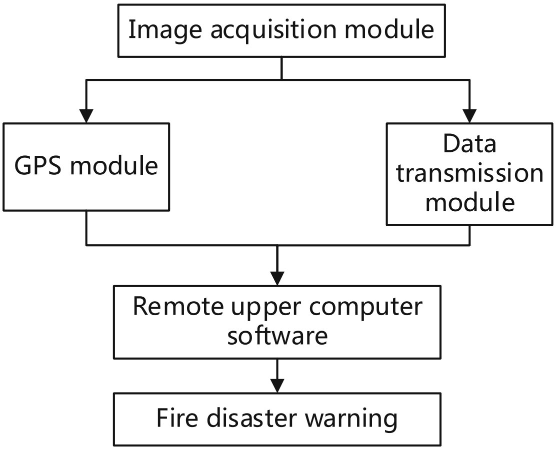

Fig. 3. The data processing flowchart of the process executed by data processing software

The communications in the proposed system enables the system to send and receive the data. This data includes various information acquired by different modules of forest fire monitoring system. This mainly includes the data interaction between the drone and the remote monitoring system. The parameters are transmitted back to the ground monitoring terminal in real time. The ground terminal realizes the control of the drone flight [18]. The entire process of data interaction between different modules is presented in Fig. 4.

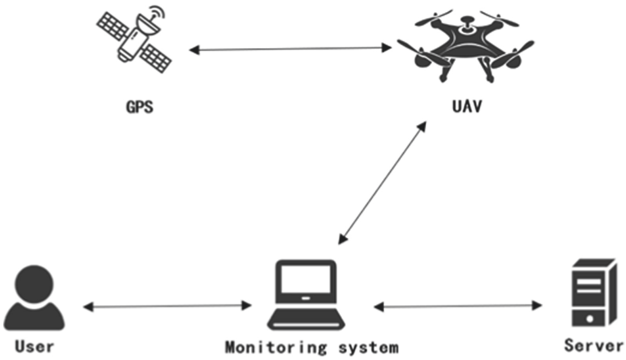

Fig. 4. The interaction between different modules of the proposed forest fire monitoring system

The communications of the drone are written using the serial port function. Every time serial communications are performed, the listening thread is opened. After monitoring is completed, the listening thread is closed. It is noticeable that if the listening thread is not closed, the next monitoring session is not executed successfully. The overall logic is to initialize the serial port for Init Port, set the open serial port and baud rate. After confirming that the serial port is opened, setup Packet Config initializes the data transmission format, frame header, frame tail, frame length, and storage byte position. When it is ensured that the listening thread has been opened, then data ready is set to TRUE. The data can only be read after confirmation. After reading the data, data ready is set to FALSE, otherwise the thread no longer works. In case that the serial port is no longer working, the port needs to be closed by using ClosePort, otherwise another serial port can-not be opened [19].

3. **Remote upper computer management system**
   The remote host computer monitoring management system has functions of image processing on one hand, and the fire danger disaster warning function of host computer software on the other. The function of image transmission and processing is to collect the aerial images of the forest captured using the PTZ camera mounted on the drone. Then, by using the image transmission system, it transmits the video in real time to the PC on the ground terminal of forest fire monitoring system. In addition, this system is also responsible to detect forest fire in the imagery data using the deep learning algorithm. The function of video capturing and transmission depends on the PTZ camera, image capturing card TC-4000 SD and image transmission system [20]. The image captured by the camera mounted on drone is transmitted to the mobile terminal of the drone remote control using image transmission system. The image is then transmitted to the image acquisition card through HDMI, and then transferred to the ground monitoring system via USB PC [21]. The image transmission and processing flow is presented in Fig. 5 and Fig. 6.

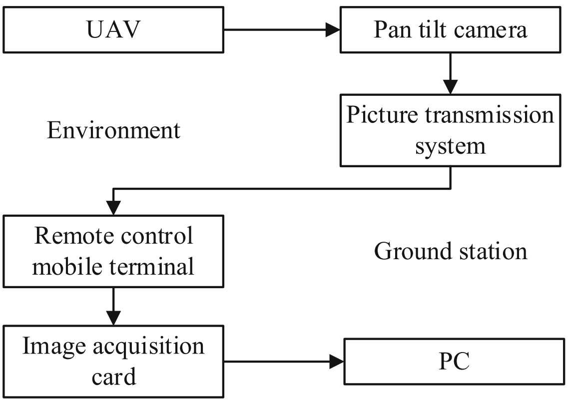

Fig. 5. The flowchart of data acquisition and transmission.

The proposed forest fire monitoring system uses DJI's Lightbridge2 image transmission system. The Lightbridge2 image transmission system supports a variety of interface outputs, such as USB, mini-HDMI and 3G-SDI. In addition, it also supports up to 1080 p/60 fps full HD output.

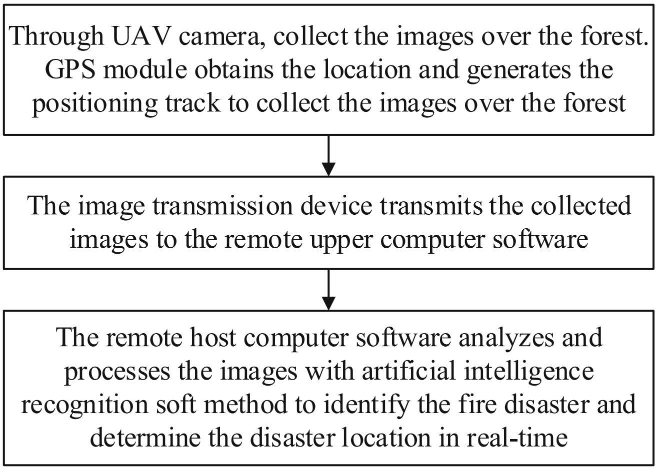

Fig. 6. The data acquisition and transmission flowchart.

The Lightbridge2 video transmission system uses wireless link dynamic adaptation technology to compensate the effects of distance, electromagnetic radiations in environment and picture quality. It automatically selects the best channel, and switches the transmission channels in case of channel disruptions. In addition, it also adjusts the video bandwidth, when necessary to ensure smooth video and effectively reduces the picture defects and interruptions. Using the deep learning algorithm, the image delay is further reduced to 50 ms when the maximum transmission distance is 5 km. The Lightbridge2 image transmission system combines high-speed processors and deep learning algorithms to make the wireless transmission of images more stable and reliable.

The modules of the remote upper computer management system include basic information module of the forest farm, image processing and early warning module, and manual data processing module. The basic information module introduces the list of state-owned forest farms in Guangdong province and the corresponding prefecture-level forestry bureau links. On this interface, it is convenient for forest staff to find the relevant forest farm information. According to the forestry bureau's portal website links, it is possible to find the local forestry bureau that belongs to a particular forest farm, and its keeps the staff abreast of the local forestry bureau's developments.

Similarly, it also has a map interface of various forest farms, which provides the geographical location of its own forest site, such as its own city and latitude and longitude, etc. This is helpful in the process of drone deployment for forest fire danger monitoring system.

On the basis of image processing module, we detect the fire incidents in the forest. In case of fire disaster detection, the system displays the geographic location and promptly alerts the forest farm staff. The signal is displayed in red for disaster warning and green for normal conditions. The fire warning interface of the monitoring system is shown in Fig. 7.

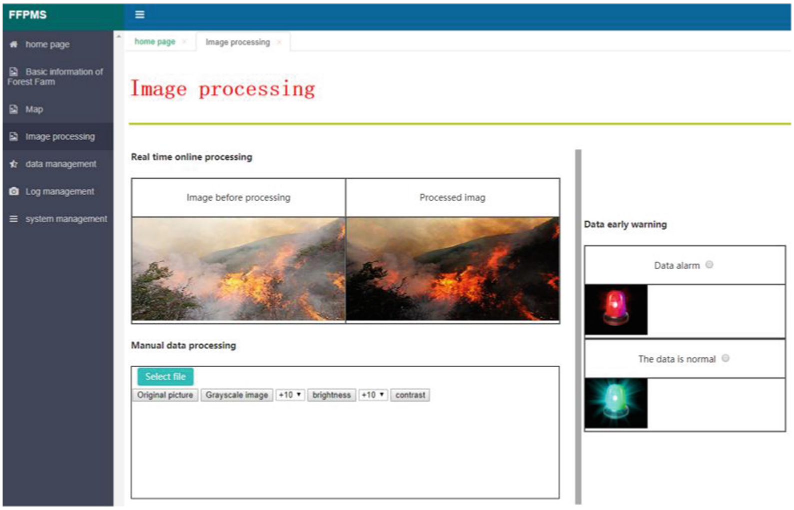

Fig. 7. The fire disaster warning interface for the proposed system.

When it is necessary to manually process the images, we perform image processing by using the manual processing interface. In addition, there is a picture management interface that is used to store pictures of forest fire prevention, and displays the pictures from the picture library according to the user's needs. It also provides the forest staff with a view of historical image data. This is presented in Fig. 8.

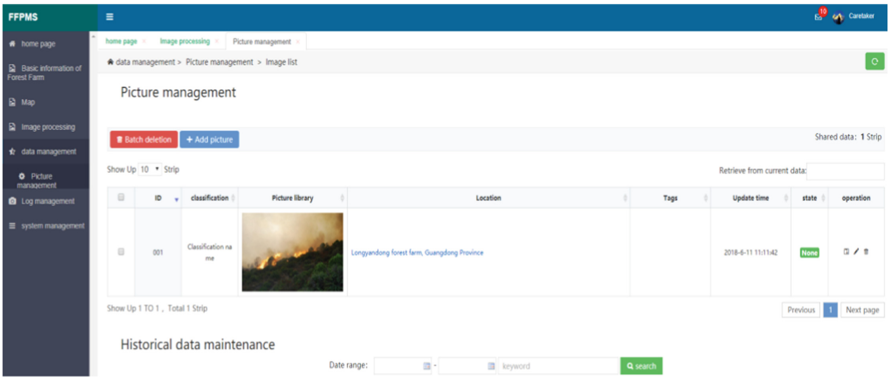

Fig. 8. The picture management interface of the proposed system.

In addition, in the log management interface, historical background data processing records are stored, and historical management operations are backed up.

3 Design of Fire Insurance Monitoring Algorithm

The design of the forest fire monitoring algorithm uses digital pattern processing and digital image processing techniques, such as image segmentation, feature extraction, image classification and recognition, etc. to accomplish the digital, automated, unmanned real-time monitoring and early warning [22].

The workflow of the forest fire monitoring algorithm is discussed below.

1) UAV equipped with visible high-definition camera is used to capture images which are transmitted to the PC on the ground monitoring system terminal via image acquisition card.
2) The ground monitoring system terminal receives the images transmitted by the drone and reads the video frame.

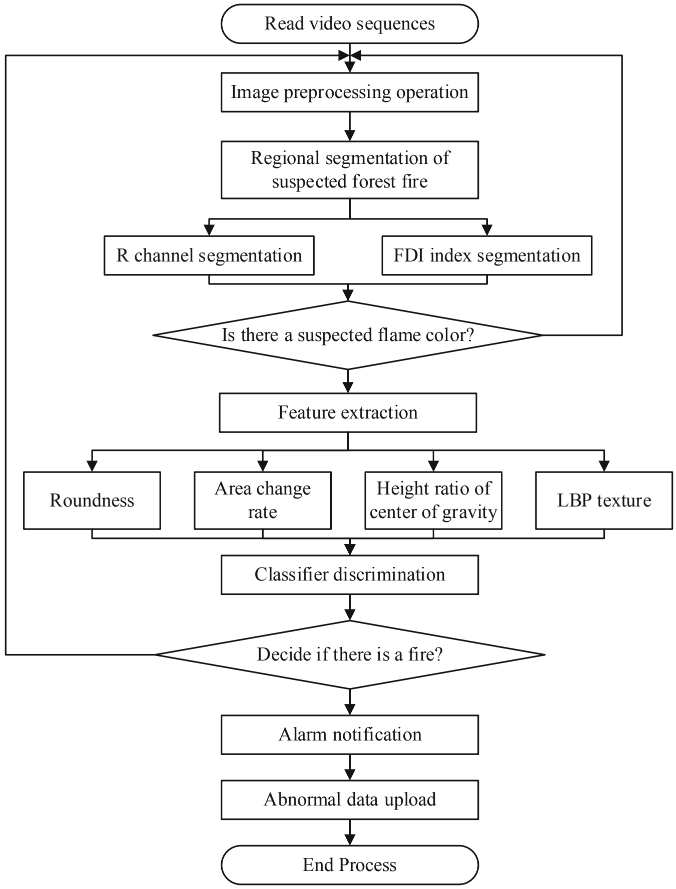

Fig. 9. The algorithm flowchart for the proposed forest fire monitoring system.

3) The acquired image may be corrupted due to interference such as noise. This interference is not conducive to forest fire monitoring and identification at later stages. Therefore, we perform image preprocessing.
4) Use the flame segmentation method based on the combination of FDI index and R channel to extract the suspected flame area.
5) Extract the dynamic and static features of the suspected forest fire color area, including circularity features, area change rate, gravity center height ratio features, and LBP texture features.
6) The extracted feature vector is subject to the trained classifier for classification and recognition to determine if a fire incident has occurred.
7) In case of fire incident, trigger the alarm device to raise an alarm and notify the relevant personnel to prepare for firefighting, otherwise continue to perform cyclic monitoring.

Figure 9 presents a flowchart of forest fire monitoring algorithm design.

4 Simulation Results and Analysis

The UAV system uses STM32 development board, integrated embedded Hash memory and RAM for program and data storage. It adopts SDK secondary development to achieve custom control and function expansion. The proposed remote monitoring system is configured with six-core Intel Core (TM) i7-8700K CPU@3.7gGHz, 16 GB RAM, and Windows 10 operating system. The algorithm is developed using OpenCV library and C++.

4.1 System Hardware Function Test

The hardware function test of the forest fire and disaster monitoring system based on deep learning and drone technology is accomplished by repeated debugging of each hardware function and long-term running test of the entire system. The purpose is to test whether the drone system works normally and whether the entire system runs successfully for a long time, etc.

4.2 System Software Function Test

Deep learning-based software tests of drone forest fire disaster monitoring system include reliability and real-time testing of the proposed system. In addition, we perform testing on various functions, such as user login test, abnormal alarm test, historical abnormal traceability test, and equipment fault prompt function, etc.

The method used for testing reliability and real-time test of the forest fire disaster monitoring algorithm is to log multiple segments of video with flames and interference videos (such as the video of car lights or people, objects, etc. that have a high similarity index with flames). The algorithm performs detection and identification on these videos and analyzes whether the accuracy rate, false alarm rate, and execution time of statistical monitoring meets the monitoring requirements [23]. Similarly, the method for testing the user login function is to test the correct and incorrect user names and passwords multiple times to ensure that the system logs in normally. In order to ensure that alarm is triggered accordingly, we test if wrong fire detection leads to triggering the alarm. In order to ensure the historical data correctness, we test if the user can query the impact of historical abnormal events and related information through software. The method used for equipment fault prompt function test is to deliberately modify normal operations of the system's equipment and check whether the equipment fault prompt occurs.

4.3 System Communication Function Test

The test of the communications of the forest fire disaster monitoring system based on the drone is tested on the basis of data interaction between the devices at different distances. The functional test results are presented in Table 1.

Table 1. The communication function testing for the proposed forest fire monitoring system

Communication distance	200 m	800 m	1400 m	2000 m	2600 m
Communication between UAV and remote server	Normal	Normal	Normal	Normal	Normal
Communication between UAV and remote controller	Normal	Normal	Normal	Normal	Normal
Image transmission	Normal	Normal	Normal	Normal	Normal

4.4 Comparison of the Results of Algorithms

4.4.1 Data Processing Speed

We consider a video of length 4 min and 19 s. There are 29 images per second, a total of 7511 images. The size of each frame is 960 × 540. We calculate the time consumed by the algorithms to complete the relevant processes. The processing speed and delay rate of the corresponding algorithms are calculated and presented in Table 2.

When the algorithm directly processes the video, it lowers the processing speed. In order to achieve real-time data processing, video frame capturing method needs to reduce the number of frames in preprocessing. When the flight speed of UAV is constant, the change of the scene information recorded by the video is limited. When the video frame is set to 5 frames per second, the inter frame difference method and background subtraction method are used to speed up the process. The processing speed of division and deep learning algorithm meets the requirements of real-time data processing. The deep learning algorithm meets the requirements of processing speed and accuracy under similar conditions.

Table 2. The completion time, processing speed and delay rate of each algorithm processing the original data.

Processing method	Processing speed	Completion time	Delay rate
Original video	29 frames/s	4 min 19 s	0%
Deep Learning algorithm	5.83 frames/s	21 min 28 s	80%
Inter frame difference method	7.12 frames/s	17 min 35 s	75.45%
Background subtraction	6.84 frames/s	18 min 18 s	76.41%
Vibe algorithm	0.85 frames/s	2 h 27 min 17 s	97.1%

4.4.2 Accuracy of Data Processing

In this experiment, different algorithms are used to process drone imagery, and the results are compared with the deep learning algorithm. The results show that the modified algorithm has advantages over other algorithms. The results of different algorithms are presented in Fig. 10 and Table 3.

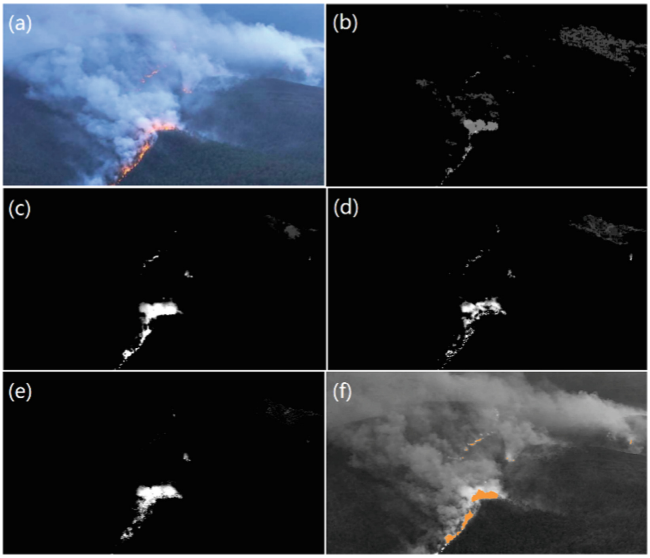

Fig. 10. The comparison among identification results of different pyrotechnic identification methods. (a) original picture; (b) deep learning algorithm; (c) inter-frame difference method; (d) background subtraction; (e) vibe algorithm; (f) manual statistics.

As presented in Fig. 10 and Table 3, the deep learning algorithm is compared with inter frame difference method, background subtraction method and Vibe algorithm. The deep learning algorithm has superior results. In Table 3, we pre-sent manual statistics which show that more accurate experimental results are obtained by manually marking the pyro-technic area.

Table 3. The comparison between identification results of different pyrotechnic identification methods.

	Deep learning algorithm	Inter frame difference method	Background subtraction	Vibe algorithm	Manual statistics
Pixel number of pyrotechnic areas	327	183	214	216	406
Number of similar pixels	2125	117	309	437	0
Miscalculation of pixel number	2386	6185	1051	3419	0
The pixel number of the result is determined	2909	6583	2336	4424	406
Relative accuracy	81%	45%	53%	53%	1
Judging accuracy	11%	3%	9%	5%	1

In this experiment, the result of the deep learning algorithm is closer to the result of manual statistics. This proves that the deep learning algorithm is better than other methods in terms of recognition accuracy. When combined with the experimental results of removing suspected fire areas, the algorithm processes the statistical results of relative decision ac-curacy and decision accuracy rate is further improved.

In addition, through the comparison of processing results of the general recognition algorithm and the deep learning algorithm, we observe inter frame difference. The method is not suitable for UAV video detection and is easily affected by the environment and motion conditions, which makes the recognition results poor. The recognition accuracy is almost 0. The comparison between the results of background subtraction and deep learning algorithm makes evident that the processing results of background subtraction method vary greatly when UAV is moving and hovering.

5 Conclusion

In this work, we propose a deep learning and drone technology-based forest fire monitoring system. Through detailed testing of the system, we ensure that the communication between various modules of the proposed system is flawless. The distance of the UAV image transmission is up to 5 km. The actual measurement range has a good transmission effect within 2 km. This transmission distance meets the requirements of forest inspection. In this experiment, different algorithms are used to process drone imagery, and the results are compared with the deep learning algorithm. The relative ac-curacy of deep learning algorithm is 81%, and the results show that the modified algorithm has advantages over other algorithms, which meets the reliability and real-time performance of forest farm fire disaster monitoring. The other functions of the system are tested and all of them function normally.

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