



SURVEILLANCE SYSTEMS FOR FOREST FIRE DETECTION USING UAV

¹Dinesh Reddy Kunduru, ²Murali Krishna Bangari, ³Sai Ganesh Karumanchi, ⁴Harish Golla,

⁵Jaya Sri Valli Medapati, ⁶Amit Kumar Thakur

^{1, 2, 3, 4, 5} Student, ⁶Professor

^{1, 2, 3, 4, 5, 6} School of Mechanical Engineering, Department of Aerospace

^{1, 2, 3, 4, 5, 6} Lovely Professional University, Phagwara, Punjab, India

Abstract: This paper is about forest fire detection and assistance by using UAVs. Various methods and algorithms used in fire detection are described. With the help of different techniques used in UAVs, determine the best effective method which can be used in UAVs based on the type of mission. Also, smoke detection methods to detect smoke to prevent false alarms, and various communication methods networks used in UAVs are described.

Index Terms: Image processing, Smoke detection, Communication networks, Self-defense strategies

I. INTRODUCTION

Forest influences both positive and negative ways for human society. Forests provide environmental support such as food, crops, fruits, raw materials (wood, fodder), and socio-economic support like energy, medical resources, ornamental resources (handicrafts, jewelry, furs, etc). It also plays an important role in the purification of water and air, climate regulation, Waste decomposition, pollination, and flood protection. However, because human activities and natural occurrences are decreasing the forest areas and their habitat. It is also the habitat for wildlife and plant species. One of the main reasons for forest decrease is because of forest fires (or) wildfires.

The natural causes of forest fires are lightning strikes, Volcanic eruptions, rock sparks, and spontaneous combustion. Human activities like campfires, bonfires, Equipment malfunction, discarding cigarettes, arson, etc., are causing forest fires. Because of drastic climate change and increasing human activities around the globe, forest fires will increase shortly. In recent years forest fires like amazon forest fires burnt nearly 3500 Square miles of areas due to global warming and climate change. More than 24 million hectares of land burned during the Australian Black summer bushfire from 2019-to 2020. Another risk factor for forests is illegal activities like smuggling, Deforestation, etc., Because increasing infrastructure and medical applications which require plants are causing deforestation.

To prevent forest fires and deforestation earlier conventional ways like human patrol, watchtowers, smoke detectors, and thermal sensors are used for decreasing damage caused by forest fires and illegal activities. But they cannot pinpoint the exact location and prevent the start of a disaster. Smoke and thermal sensors cannot provide the size and location of fires. Human patrols are affected by fatigue and monotony, Satellite images have poor resolution and insufficient data for early detection. These methods cannot provide real-time data for controlling and monitoring the situation in the forests. They can also be dangerous for human lives (firefighters) and costly. Rapid advances in Technologies like computer engineering, digital cameras, Electronics, and the growth of UAVs have allowed for early-stage detection, controlling, and prevention of forest fires. Advancements in UAVS made it easy to prevent and control the situations for firefighters and forest officials. Usage of sensors for fire detection, camera for viewing the situations, GPS for pinpointing the location. Nowadays UAVs are made smaller and cheaper which is cost-efficient for providing real-time updates.

1.1 Forest fire monitoring by UAV

The general methodology of UAV-based forest fire monitoring is simple; a single UAV or a fleet of cooperative UAVs fly over high-risk zones in a forest and capture images using their onboard optoelectronic sensors. The captured visual or infrared images will be processed onboard or through a ground station and identify the presence or absence of fire. If a fire is confirmed then an alarm is sent to the nearby fire stations along with the location and size of the fire. The components of the monitoring system are drones, sensors or cameras, ground stations, or computers with machine learning software.

1.1.1 Drone selection

UAVs can be classified as fixed-wing or rotating wings, a fixed-wing UAV is cheap, can carry a large salary, and can achieve high altitude and long endurance. However, the rotating wing UAVs are flexible, easily maneuverable, and capable of flying. The conditions for the drone with the combination of the camera were: good image quality, effective long-distance flight, durability, and availability of advanced flight controls.

The UAV is about 1 meter wide, weighs about one kilogram, and has a quiet electric drive (4 brushless- and gearless DC motors). Flight time is approx. 25 min depending on the weight of the payload. The maximum speed of AR100-B is 10 m / s (36 km / h = 5 Bft), the maximum air load is 8 m / s (28.8 km / h = 5 Bft)[3]. It can be flown without any pilot experience. Data transfer and real-time control are possible with RF devices. Telemetry data is displayed live on the base station and can be tracked on a map in real-time. All processing detection and avoidance collisions occur automatically on Air Robot



Fig 1. DJI Mavic pro- [3]

1.1.2 Sensors or camera

A sensor is a device that generates an output signal to hear a visual object. In general, a sensor is a device, module, machine, or subcontractor that detects events or changes in its location and transmits information to other electronic devices, usually a computer processor. Sensors are often used with other electrical objects.

Three sensors were used in this study which is noted in table 1. All sensors were mounted on a nadir, that is, downward from the plane. The first sensor used in this study was the ITRES micro-TABI (TABI), which is a broadband, broad-spectrum, high-resolution cryo-cooled Push frame. This sensor has a reported spacecraft of 0.7 m and a flight line of 1,200 m at a speed of 56.58 meters per second (110 knots) and a height of 1,730 m AGL. This sensor is considered to be an infrared (MWIR) sensor in the middle of the waves as it has a visible width of 3.7–4.8 mm. The second sensor, the FLIR Duo Pro R (Pro) is a hot camera with dual HD sensors. Combined with high-resolution radiometric photo resolution and a 4K color camera. This sensor has an uninsulated Vox Microbolometer [20]. This sensor is considered a thermal infrared (TIR) sensor as it has a spectral diameter of 7.5–13.5 mm. Finally, the FLIR Duo (Duo) was the third sensor used throughout the study. This is a hot and cold radiometric image designed for professional drone applications. This sensor has been discontinued since 1 November 2018. This sensor is considered a hot infrared (TIR) sensor as it has a visible width of 7.5–13.5 mm.



Fig 2: sensors - [20]

Table 1: Sensor table comparison- [20]

Price	Approx. \$100,000	Approx. \$6,000	Approx. \$3,000
Dimensions (mm)	100 * 230 *250	85*81.3*68.5	41*59 *29.6
Weight (g)	3,800	325	84
Spectral range (mm)	3.7–4.8	7.5–13.5	7.5–13.5
Spectral channel	1	1	1
Max frame rate (Hz)	90-110	30	8.3
Operating temperature (C)	0–40	-20 to 50	0-50
Thermal measurement accuracy	Not Available	±5 C or 5% of readings in the –25 to þ135 C range ±20 C or 20% of readings in the –40 to þ550 C range	±5 C or 5% of reading

Field of view (°)	40	25–45 (depending on lens)	57*44 (90 on visible camera)
Maximum altitude	10,000 ft/4,500 m	38,000 ft	12,000ft
Sensor resolution	640*512	4,000*3,000 (thermal 640*512)	1,920*1,080 (thermal 160*120)
GPS	GNSS or MEMS (external)	GLONASS	None
Output format	BIP (ENVI compatible)	Analog/Digital video (1080p mov/ tiff/jpg)	Analog/Digital video (1080p mov/ tiff/jpg)

1.1.3 Image processing:

After the images are captured using cameras or sensors. The images are processed to determine the location of the fire in the images captured by different techniques and algorithms. The based rule is practical and simple is the complexity of the calculation. Proposed rules apply to RGB aircraft. Images have red, green, and green planes. Devices can represent color in a digital environment based on the data provided. In the fire circuit images, R-plane has much higher values than the G and B planes.

Seven pixels rules for finding fire pixels:

- 1) $R1(x, y) = \{1, \text{if } R(x, y) > G(x, y) > B(x, y); 0, \text{otherwise}\}$
- 2) $R2(x, y) = \{1, \text{if } (R(x, y) > 190) \cap (G(x, y) > 100) \cap (B(x, y) > 140); 0, \text{otherwise}\}$
- 3) $R3(x, y) = \{1, \text{if } Y(x, y) \geq C_b(x, y); 0, \text{otherwise}\}$
- 4) $R4(x, y) = \{1, \text{if } C_r(x, y) \geq C_b(x, y); 0, \text{otherwise}\}$
- 5) $R5(x, y) = \{1 \text{ if } (Y(x, y) \geq Y_{dial}(x, y)) \cap (C_b(x, y) \leq C_{b \text{ mean}}(x, y)) \cap (C_r(x, y) \geq C_{r \text{ mean}}(x, y)); 0, \text{otherwise}\}$
- 6) $R6(x, y) = \{1, \text{if } (C_b(x, y) - C_r(x, y) \geq Th); 0, \text{otherwise}\}$
- 7) $R7(x, y) = \{1, \text{if } (C_b(x, y) \leq 120) \cap (C_r(x, y) \geq 150); 0, \text{otherwise}\}$

set limit values so that pixels can catch fire on photos and view multiple image data. Give them the rule to get the pixel fire in place (x, y) links RGB planes are converted to Y, Cb, Cr, color space. It helps to find fireplaces in Y, Cb, and Cr color space where Y shines, Cb, Cr, with chrominance blue and red chrominance. The firing circuit is usually the light circuit in a given image. Part of Y. TH is precisely determined by the ROC (acquisition of the acquisition characteristic curve). The ROC curve is obtained by checking the different values of Th (from 1 to 100) over 100 color images. By using the ROC curve, the proposed method achieves 99% fire detection and a false alarm level of 14%. The algorithm is built-in python language to detect fire circuits by image pixels. NumPy API and open CV are used for calculation. These algorithms are captured on videos captured by UAVs with cameras or sensors. Videos are framed so that each frame is converted to HSV. Hue Saturation color space is better than RGB color space for image processing. The color value is defined by setting the upper and lower parameters to determine the required pixels. Prices are used independently and the required colors are reflected in the range used. The advanced algorithm is used in Raspberry pi in UAVs. Real-time fire detection method based on computer vision detection techniques. First, the images are found in the RGB color space and then converted to CIE L * a * b color space. Using CIE color L * a * b controls that fire pixels are detected in images. In CIE L * a * b some dimensions or parameters are given based on the different pixels of the image or the intensity obtained by the test number of the images. To find the moving pixels use a binary frames differential map to find the moving and writing pixels in the pictures. They have added background registration to update the package bath containing multiple stored frames. This calibration process is used in various video tracking to detect fire in moving frames in a variety of natural environments. It got a 99.8% detection rate on video tracking. This method cannot detect or remove smoke screens from images that may give false alarms or fail smoke conditions. However, the fire is detected before the smoke produces [26]. Fig3 shows the flow chart based on the rule of the algorithm, Figure 4 Displays the flow chart for processing the computer vision method.

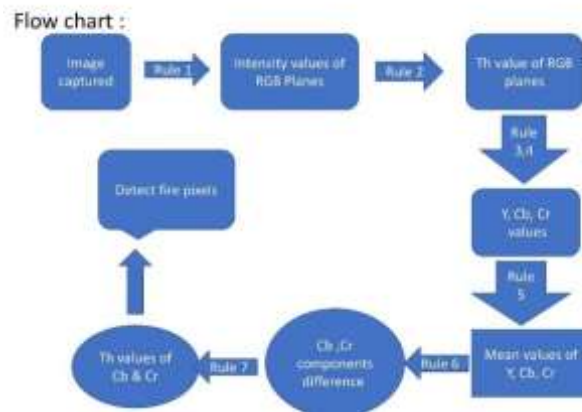


Fig 3: Rule-based algorithm flow chart. - [5]

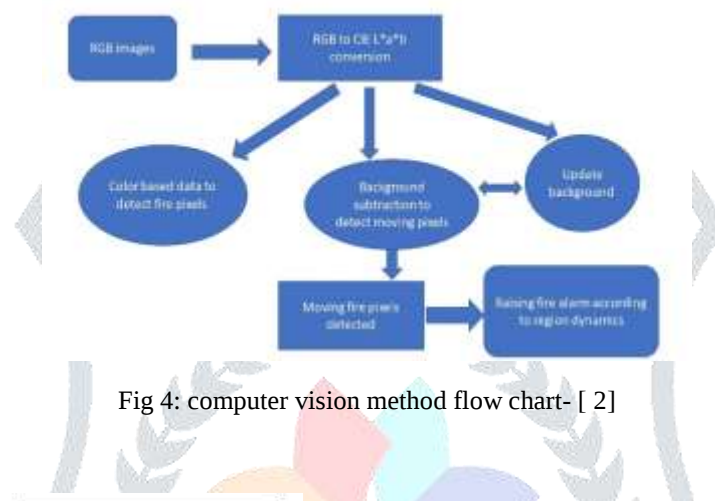


Fig 4: computer vision method flow chart- [2]

1.1.4 Algorithm outcomes:

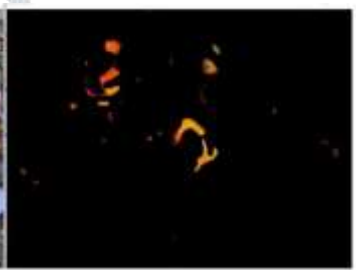


Figure 5: image algorithm result- [5]

Figure 6: Computer vision result - [26]

The algorithm can detect fire in images but it cannot remove smoke screens in images which may give a false alarm rate. To detect smoke in images.

1.1.5 Smoke detection:

There are certain rules applied for the correction of smoke areas. Smoke detection is similar to fire detection in the chromatin and motion features of smoke are exercised for smoke disclosure. The area which is smoke surrounded is subdivided by analyzing color properties. The rules which are applied are as follows:

1) Smoke color segmentation:

Identifying smoke is quite difficult when compared to fire. Smoke generally has different color properties. Sometimes the color range of smoke varies from milky white to deep gray. This color property makes it difficult to identify some when compared to fire. Based on two rules smoke generally has a smoke color mask in RGB and Y Cb Cr color space.

Rule 9	$R(x, y) - G(x, y) \leq \theta$ $R(x, y) - B(x, y) \leq \theta$ $B(x, y) - G(x, y) \leq \theta$
Rule 10	$121 \leq Cb(x, y) \leq 135 \text{ and } 121 \leq Cr(x, y) \leq 135$

Algorithm rules [23]

Smoke areas are generally differentiated into two types. They are further divided into two main categories which are identified by checking the videos recorded in unmanned aerial vehicles. If in case the forest got affected by a huge fire accident with a long burning time the smoke becomes dense and milky white. By the observation of smoke in RGB color space, the color components of Red, Green, and Blue are similar. The smoke components can be processed using Rule 1 mentioned in the above table. The α is set at a constant value of 15 based on our database. If in case the forest got affected by a small fire accident with a short burning time the smoke becomes translucent and transparent and further mixed with the background color and becomes grayish. By examining the color properties of C_b and C_r components. $Y C_b C_r$ color space components are extracted by using rule 2. The requirement of both the lower threshold and upper thresholds is required due to the wide color range of smoke. The threshold values are acquired based on the database of the smoke forest fire.

Algorithm 3 Smoke filter Extraction

1: Input: Current frame.
 2: Apply Rule 9, obtain Mask 4 in RGB color space.
 3: Convert current frame to YCbCr color space.
 4: Apply Rule 10, obtain Mask 5 in YCbCr color space.
 5: Output: Smoke-colored Mask = Mask 4 OR Mask 5.

Algorithm- [23]

Based on the above table, we compound two color masks derived from two color spaces of RGB and YCbCr by using OR Boolean to balance both the smoke categories.

2) Smoke Motion Extracting:

Smoke is generally brought out by its vigorous characteristics similar to fire. Fire can be extracted from its dynamic background by taking advantage of disordered motion. We cannot apply the same algorithm to obtain smoke motion detection.

Algorithm 4 Smoke motion extraction

1: Input: Current frame and previous frame.
 2: Solving both equations (5) and (6) to obtain u, v , then, calculating amplitude and direction of velocity vectors.
 3: Calculation mean value of all velocity vectors.
 4: If magnitude of velocity vector of pixel (x, y) is upper than $\beta=20$ and phase of it also satisfies threshold $\gamma=100$.
 5: Pixel (x, y) belongs to dynamic area.
 6: Else
 7: Pixel (x, y) belongs to static area.
 8: End if.

Algorithm - [23]

The smoke picture elements from the aerial video travel from one certain direction or are nearly referenced to UAVs these states whether the UAV direction and the smoke direction are the same. Based on above algorithm 2 which uses the Lucas-Kanade method for calculating optical flow, in algorithm 4 of smoke motion identification, we generally give two threshold values for both magnitude and phase of the velocity vector of smoke pixels. By using equations 5 and 6 we can derive the values of velocity vectors of pixels in the current frame. Then the chaos vector is obtained by subtracting the vector of each pixel by the average velocity vector of all the pixels in the frame. Two predefined lower thresholds of $\beta=20$ and $\gamma=100$ are then applied to the magnitude and phase of the chaos vector, respectively. The threshold values are selected after analyzing the motion of smoke in some aerial videos. Smoke areas that are not moving in the same direction as the UAVs are highlighted by creating the smoke foreground mask.

3)Smoke Area Correcting:

Based on the results obtained from white smoke motion detection the steps displayed the borderline of the smoke moving region. The smoke components under the region usually cannot be identified due to their slow movement. Because of this, we have to collide the results of two steps of color motion segmentation by rules. If a smoke-colored area is covered by a borderline pixel of smoke foreground mask, OR Boolean is used to connect all smoke pixels. If in case the smoke color pixels AND Boolean is used to cover both smoke regions. In the final step, we use morphological close to smooth the results before finding a convex hull to draw a bounding box for output presenting. Fig. (7) presents the step-by-step results of our smoke detection scheme. In Fig. 7 (c) and (d), two-color masks reflect different color properties of smoke and are combined to get a smoke-colored mask in Fig. 7 (e). Smoke-colored pixels are not fully detected due to their translucent color. The smoke moving pixels are extracted using a smoke foreground mask obtained in Fig. 7 (f). This mask shows our failure to detect smoke pixels that are nearly in a stop state. After applying the rules, a smoke correcting mask is created in Fig. 7 (g) to filter out detected smoke.

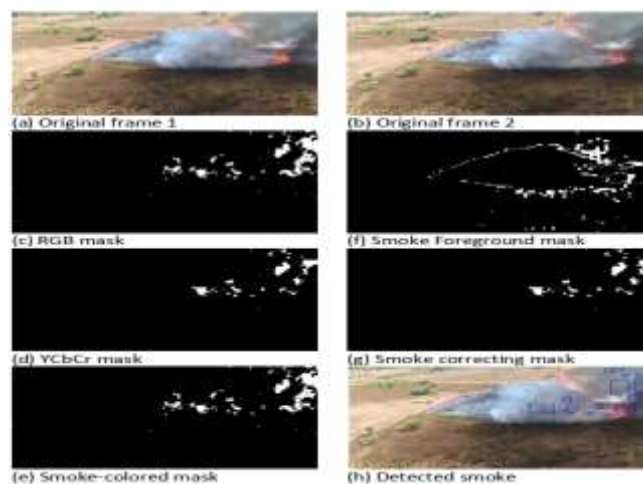


Fig 7: smoke results- [23]

II. COMMUNICATION NETWORKS IN UAVS:

Once the fire has been confirmed by the UAVs, the next task is to provide important initial information to firefighters and relevant authorities, namely the location and the size of the fire. UAVs are usually equipped with IMU and GPS sensors that allow ground stations to estimate their location and position.

2.1 Convolutional Neural Network

The flowchart is a traditional way of finding fire and the CNN-based acquisition method

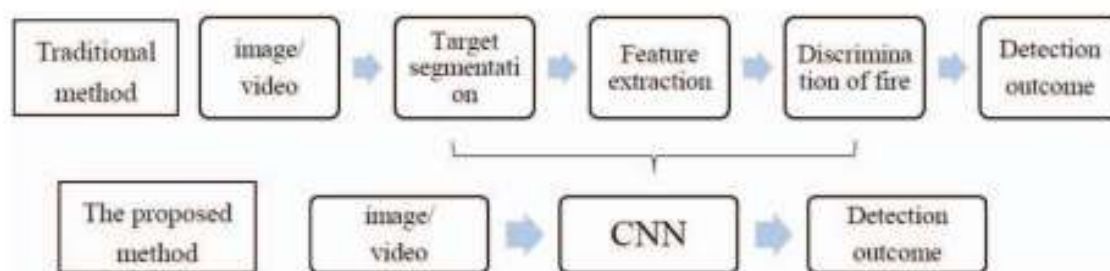


Fig 8: Convolutional flow chart 1- [10]

Video images are often affected by environment detection and uneven lighting during the detection process, as well as pre-processing functions such as image enhancement and filtering, were required before acquisition.[10] In this paper, histogram comparisons are used for the image development and a local measurement method is used for sound filtering. In addition, to simultaneously discover smoke and flame, the network of the proposed structure in has been improved. System flow received in this paper

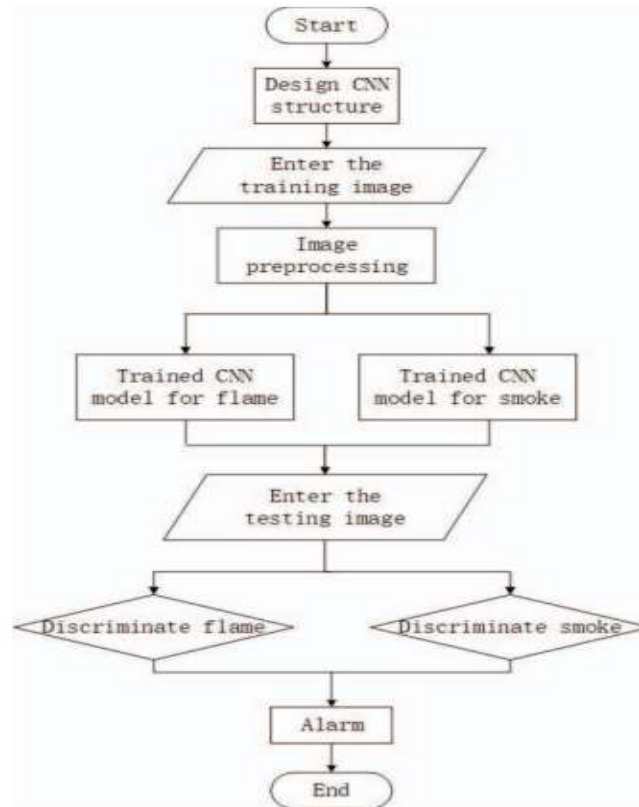


Fig 9: Convolutional Flow chart-2 - [10]

2.2 Detection in Infrared Image of Unmanned Aerial Vehicle Platform

In the infrared image, pixel light associated with high flame smoke is very high, and a feature of the maximum pixel value can successfully represent the point of fire. If you are considering emergency disaster relief, a simple threshold to distinguish threshold is used here to improve algorithm compatibility [9]. The process is as follows:

- 1) Double the pixel value, count the number of pixel values;
- 2) Adjust the flexibility of the separation limit in terms of a repeated pixel value and a number of the value of each pixel;
- 3) Set the pixel grayscale larger than the limit 255;
- 4) Maximum adjustment area by 255-pixel value in the picture the effect of finding flames;
- 5) Flame formation is not uncommon as the surrounding area is relatively large. We can use this feature to remove false alarms.

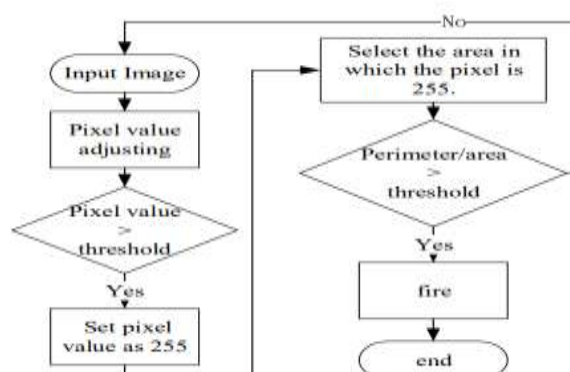


Fig 10: detection image flow chart - [9]

2.3 General Forest Fire Networking System

The standard UAV-based forest fire monitoring system is simple; A single UAV or a series of collaborative UAVs fly to high-risk areas in the jungle and capture images using their mounted optoelectronic sensors. Visual or infrared images will be processed on a board or subway and detect the presence or absence of a fire. Once the fire has been confirmed then an alarm is sent to the nearest fire station and the location and magnitude of the fire. Three basic components of the UAV-based forest fire monitoring system: vehicle, sensors, and sub-station.

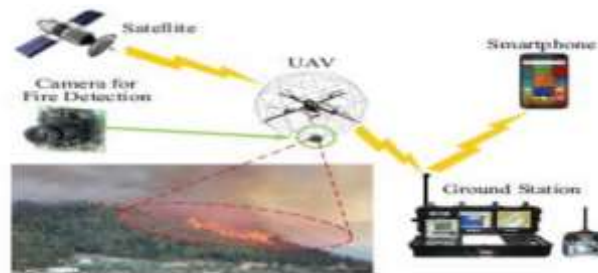


Fig 10: General network system- [8]

Depending on the type of aircraft, UAVs can be classified as fixed-wing or rotating wings. Fixed-wing aircraft are cheaper, can carry more load, and can achieve higher altitudes and longer endurance. However, UAV rotating wings are flexible, controllable, and powerful. The payload attached to the UAV contains similar sensors, internal measurement units (IMU), GPS, visual camera, Infrared camera, and transmission-reception units. IMU as well GPS is useful to provide location information for UAVs [8]. Visual cameras and various infrared cameras wavelengths are used to obtain images. The payload also contains the transmission and receiving units as horns that allow communication between UAVs and between UAVs and sub-station. The sub-station or decision support system (DSS) is a computer or portable computer that maintains vehicle communications, obtains information sent by UAVs, processes imagery, makes the necessary decisions and statistics, and communicates with the relevant authorities. Selecting the type of aircraft or components of the payload depends on the type of work being performed. In the presentations, some tests and operations use only a rotating wing, a fixed-wing only, or a combination of both types of aircraft. The same idea applies to sensors where there is a reported test with just a visual camera, infrared camera, or a combination of cameras. Finding the right combination of aircraft and a sensor depends on the length of the equipment, the complexity, and the budget

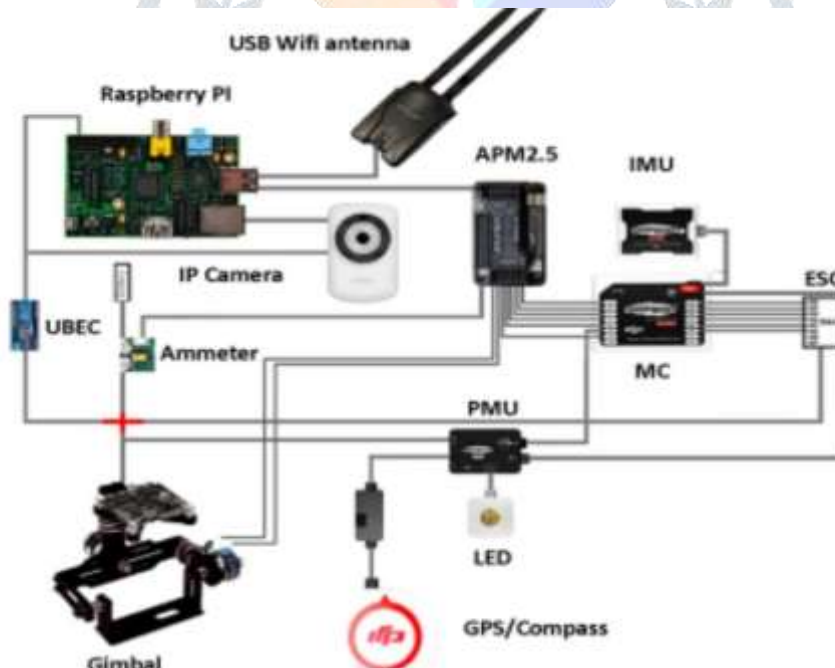


Fig 11: Wiring diagram between electronic components in UAVs - [26]

The figure shows different electronic components connections used in UAVs. The electronic components differ from mission to mission, for real-time detection it is better to use IMU (inertial measurement unit) or thermal sensors rather than cameras.

III. UAV SELF DEFENSE STRATEGIES:

1)Fire Prevention: The Fire Prevention Method prevents UAVs from approaching areas where temperatures are not safe in UAVs. This means that the safety of the UAV is more important than for any given purpose: while on duty, the UAV maintains its temperature range, and if it exceeds the set limit, it will calculate the opposite path in a way that allows it to continue to hear firefighters safely.

2)Drone Replacement: When a single UAV battery reaches 40% or less (user-friendly), a message is sent to Ground Station requesting another available UAV to replace it. This exchange only takes place when a UAV is available outside the assigned equipment. If no new UAV is available, the UAV will simply return home to recharge.

3)Collision Resistance System: The Anti-Collision System calculates whether there is a UAV on the road between one current and one UAV position. The algorithm adds extra margins along the path of 0.5 meters on each side. If the UAV is nearby but does not cross the line, there is no damage, as the safety area is a rectangle 1 meter wide and long between its current and next location.

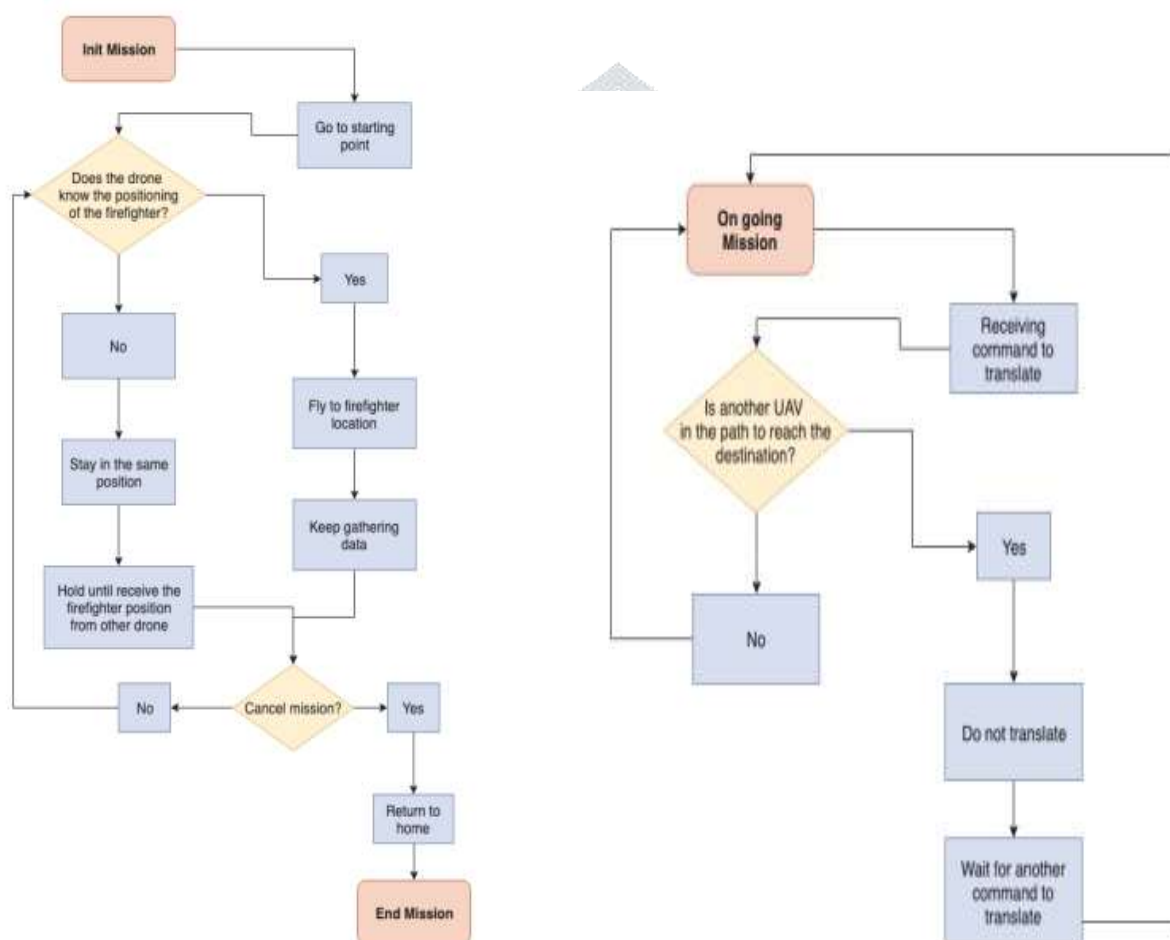


Fig 12: Collision resistance flow chart - [1]

If the UAV is on the way another UAV has calculated, it is not translating and waiting for a new command. If the new command is the same, and another UAV is out of the way, the translation continues, however, FANET may change and the command will eventually be different (elsewhere). While the UAV is waiting for another command, the network will not stop, as firefighters continue to move and other UAVs also continue to move, making the network more flexible and not blocking the road most of the time

IV. ACKNOWLEDGEMENT

We thank the Lovely Professional University for giving us this opportunity and our professor for guiding us in the research paper.

V. CONCLUSION:

We can see different systems used for forest fire detection the best method would be using the rotary-wing drone which provides high maneuverability and long-range with FLIR duo pro R which is low-cost high altitude and sensor resolution which provides better images using computer vision image processing it can detect fire areas in the forest by using communication network mentioned above it can send a response to the fire department. It is not reliable enough to rely on a single UAV for fire

protection operations. Forests cover a large area; wildfires can spread for miles and UAVs can be the victim of electrical and mechanical faults. Therefore, with a complete system that can provide continuous and reliable monitoring, it is best to have a team of UAVs working together for fast response and assistance.

REFERENCES:

- [1] Üstündağ, Aybike, and Çetin Genser. "Control of automatic fire extinguishing operation for 5 forest areas with SCADA." In *2021 5th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, pp. 535-538. IEEE, 2021.
- [2] Celik, Turgay. "Fast and efficient method for fire detection using image processing." *ETRI journal* 32, no. 6 (2010): 881-890.
- [3] Allauddin, Md Saif, G. Sai Kiran, GSS Raj Kiran, G. Srinivas, G. Uma Ratna Mouli, and P. Vishnu Prasad. "Development of a surveillance system for forest fire detection and monitoring using drones." In *IGARSS 2019-2019 IEEE International Geoscience and Remote Sensing Symposium*, pp. 9361-9363. IEEE, 2019.
- [4] Wu, Hao, Deyang Wu, and Jinsong Zhao. "An intelligent fire detection approach through cameras based on computer Vision methods." *Process Safety and Environmental Protection* 127 (2019): 245-256.
- [5] Vipin, V. "Image processing-based forest fire detection." *International Journal of Emerging Technology and Advanced Engineering* 2, no. 2 (2012): 87-95.
- [6] Moloo, Raj Kishen, and Varun Kumar Dig umber. "Low-cost mobile GPS tracking solution." In *2011 International Conference on Business Computing and Global Informatization*, pp. 516-519. IEEE, 2011.
- [7] Krull, Wolfgang, Robert Tubera, Ingolf Willms, Helmut Essen, and Nora Von Wahl. "Early forest fire detection and Verification using optical smoke, gas and microwave sensors." *Procedia Engineering* 45 (2012): 584-594.
- [8] Saadat, Md Nazmus, and Mohd Nizam Husen. "An application framework for forest fire and haze detection with data acquisition using unmanned aerial vehicles." In *Proceedings of the 12th International Conference on Ubiquitous Information Management and Communication*, pp. 1-7. 2018.
- [9] Hendel, Isabelle-Gabriele, and Gregory M. Ross. "Efficacy of remote sensing in early forest fire detection: A thermal sensor comparison." *Canadian Journal of Remote Sensing* 46, no. 4 (2020): 414-428.
- [10] Zhang, Lan, Bing Wang, Weilong Peng, Chao Li, Zeping Lu, and Yan Guo. "A method for forest fire detection using UAV." *Advanced Science and Technology Letters* 81 (2015): 69-74.
- [11] Yeom, Junho, Youkyung Han, Taeheon Kim, and Yongmin Kim. "Forest fire damage assessment using UAV images: A case study on Goseong Sokcho Forest fire in 2019." *Journal of the Korean Society of Surveying, Geodesy, Photogrammetry and Cartography* 37, no. 5 (2019): 351-357.
- [12] Chen, Yanhong, Youmin Zhang, Jing Xin, Guangyi Wang, Lingxia Mu, Yingmin Yi, Han Liu, and Ding Liu. "UAVImage-based forest fire detection approach using convolutional neural network." In *2019 14th IEEE conference on industrial electronics and applications (ICIEA)*, pp. 2118-2123. IEEE, 2019.
- [13] Sherstjuk, Vladimir, Maryna Zharikova, and Igor Sokol. "Forest fire monitoring system based on UAV team, remote sensing, and image processing." In *2018 IEEE Second International Conference on Data Stream Mining & Processing (DSMP)*, pp. 590-594. IEEE, 2018.
- [14] Hristov, Georgi, Jordan Raychev, Diyana Kinaneva, and Plamen Zahariev. "Emerging methods for early detection of forest fires using unmanned aerial vehicles and lorawan sensor networks." In *2018 28th EAEEIE Annual Conference (EAEEIE)*, pp. 1-9. IEEE, 2018.
- [15] Kinaneva, Diyana, Georgi Hristov, Jordan Raychev, and Plamen Zahariev. "Early forest fire detection using drones and artificial intelligence." In *2019 42nd International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, pp. 1060-1065. IEEE, 2019.
- [16] Shin, Jung-il, Won-woo Seo, Taejung Kim, Joowon Park, and Choong-shik Woo. "Using UAV multispectral images for classification of forest burn severity—A case study of the 2019 Gangneung Forest fire." *Forests* 10, no. 11 (2019): 1025.
- [17] Martínez-de Dios, José Ramiro, Luis Merino, Fernando Caballero, and Anibal Ollero. "Automatic forest-fire measuring using ground stations and unmanned aerial systems." *Sensors* 11, no. 6 (2011): 6328-6353.
- [18] Dafallah, Hind Abdalsalam Abdallah. "Design and implementation of an accurate real time GPS tracking system." In *The Third International Conference on e-Technologies and Networks for Development (ICeND2014)*, pp. 183-188. IEEE, 2014.
- [19] Saadat, Md Nazmus, and Mohd Nizam Husen. "An application framework for forest fire and haze detection with data acquisition using unmanned aerial vehicles." In *Proceedings of the 12th International Conference on Ubiquitous Information Management and Communication*, pp. 1-7. 2018.
- [20] Hendel, Isabelle-Gabriele, and Gregory M. Ross. "Efficacy of remote sensing in early forest fire detection: A thermal sensor comparison." *Canadian Journal of Remote Sensing* 46, no. 4 (2020): 414-428.
- [21] Zhang, Lan, Bing Wang, Weilong Peng, Chao Li, Zeping Lu, and Yan Guo. "A method for forest fire detection using UAV." *Advanced Science and Technology Letters* 81 (2015): 69-74.
- [22] Casbeer, David W., Randal W. Beard, Timothy W. McLain, Sai-Ming Li, and Raman K. Mehra. "Forest fire monitoring with multiple small UAVs." In *Proceedings of the 2005, American Control Conference, 2005.*, pp. 3530-3535. IEEE, 2005.

- [23] Dang-Ngoc, Hanh, and Hieu Nguyen-Trung. "Aerial forest fire surveillance-evaluation of forest fire detection model using aerial videos." In *2019 International Conference on Advanced Technologies for Communications (ATC)*, pp. 142-148. IEEE, 2019.
- [24] Akhloufi , Moulay A., Andy Couturier, and Nicolás A. Castro. "Unmanned aerial vehicles for wildland fires: Sensing perception, cooperation and assistance." *Drones* 5, no. 1 (2021): 15.
- [25] Ghamry , Khaled A., Mohamed A. Kamel, and Youmin Zhang. "Cooperative forest monitoring and fire detection using a team of UAVs-UGVs." In *2016 International Conference on Unmanned Aircraft Systems (ICUAS)*, pp. 1206-1211. IEEE, 2016.
- [26] Chamoso, Pablo, Alfonso González-Briones, Fernando De La Prieta, and Juan M. Corchado. "Computer vision system for fire detection and report using UAVs." In *RSFF*, pp. 40-49. 2018.

