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The Design and Development of a Machine Learning Wildfire UAV Swarm Algorithm: IPCA

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Abstract— **With the frequency of wildfires increasing, specifically across the Western United States, there exists a need for the reduction in damage to both the community and environment. Many urbanized areas and communities have been significantly affected or demolished by the rapid and devastating spread of recent wildfires. As the impact of global warming increases and the weather patterns begin to vary, the ability to contain a wildfire quickly begins to pose a challenge. While current solutions exist on the market, they are simply not designed for the increasingly faster spread because of ever-changing weather patterns. Additionally, the need for firefighters to have specialized experience has caused a rift between the number of those who can contain fires and the number of fires to be contained. The purpose of this project is the development of a machine learning wildfire UAV swam algorithm to allow the rapid and real time update of containment line calculations/visualizations to allow first-responders to effectively and quickly contain wildfires. By measuring major heat signatures, the UAV system can identify wildfires, and through TensorFlow analysis of wind patterns and environmental markers, make feedback decisions of where to search for spot fires. The combination of wildfires and the spot fires that may arise, result in a containment line visualization with coordinates for first responders to utilize. The goal of the IPCA is a functional autonomous system that can provide the prediction and aid for first responders to have another line of defense against the spread of wildfires into residential and urbanized areas.**

Keywords: UAV, wildfire, autonomous systems, drone, TensorFlow, Machine Learning

I. INTRODUCTION

As climate change continues to affect the planet in numerous ways, a major consequence has been a rapid increase in wildfires, most recently effecting Western United States, with major fires this year spreading across the southern California coast [1]. As the temperature of the Earth becomes warmer, conditions on the ground and in the air have become drier, resulting in more ignitions and quicker spread. This is the cause of these major fires which continue to have a positive frequency trend [2]. Not only has there been an increase in the number of wildfires in California over the last century, the size of these fires has also increased. According to a study done surrounding major fires occurring in California in 2020, the frequency and size of wildfires were compared to past environmental trends seen in the early 20th century. The findings revealed, “such extreme fire events are not unknown to historically, and what stands out as distinctly new is the increased number of large fires in the last couple of years, most prominently in 2020” [3].

With the recent increase in population, many forests and previously uninhabited areas have become the target for new developments and urbanization. However, the inhabitation of these areas has caused a significant creation of WUI’s, which in combination with the ever-increasing risk of wildfires has put many lives, people, and property in danger. A WUI or wildland-urban interface is “the area where houses and wildland vegetation meet or intermingle”, when combined with increasing global warming effects, these areas are where “wildfire problems are most pronounced” [4]. Wildfires occurring in WUI areas is nothing new. Often, fires that begin or occur in WUI’s have spread into urbanized areas, putting more lives and property at risk. In the 2017 Tubbs Fire, which originated in a WUI, spread to Coffey Park in Santa Rosa, CA that was subsequently destroyed, “sits outside the edge of the interface” and one the fire spread out of the WUI and into Coffey Park, “the fire burned 0.9 mi beyond the interface limit into developed lands” [5]. This resulted in not only the destruction of the land but also homes and loss of life. Of the total 36,807 acres that were burned in the Tubbs Fire, 5,643 structures were destroyed, half of which were homes in Santa Rosa. Additionally, nine people in Santa Rosa alone lost their lives. In total, the economic loss from the fire was estimated to be around $1.2 billion [6]. The overall impact from WUI’s is non-ignorable, as it not only affects the people inhabiting them, but those inhabiting the surrounding areas as well which are often more densely populated, leading to a greater risk to life and property. “More than forty million homes worth approximately $187 billion in the U.S. are currently at a high risk of destruction due to wildfires” [7]. The growing presence of WUI’s has resulted in an increasing in properties now deemed high risk.

Currently, the systems in place for fighting and containing fires are effective for small scale fires, “despite spending approximately $3.7 billion annually on fire suppression” [7]. Using structures like the fire department and their apparatuses, smaller residential fires can be effectively controlled. Other methods for large wildfires are using large air tankers or single engine planes to spread either water of fire retardant across large areas, preventing larger fires from moving into residential areas. In the January 2025 California fires, fire departments used any individuals with firefighting experience to fight rapidly spreading fires

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as a last resort. They utilized retired career or volunteer firefighters or even prisoners as an emergency means to put these fires out. According to California's Department of Corrections and Rehabilitation said "1,015 Fire Camp firefighters have been working around the clock cutting fire lines and removing fuel from behind structures to slow fire spread" [7]. This is not only incredibly controversial since these individuals are being put at incredible risk, but it reveals how needed a new and more effective form for fire prevention and containment equipment is needed.

This paper describes a system that utilizes drones and a machine learning model to assist firefighters in the fighting of wildfires, through the drawing of containment lines. Testing and analysis of this system provides a foundation for future scaling to industrial and professional drones to allow for less risk to life, faster containment times, and limit destruction of both environment and property.

II. METHODS AND MATERIALS

The modules of this project include the Crazyflie drones, the drone native CfClient program and controller, and the TensorFlow machine learning model.

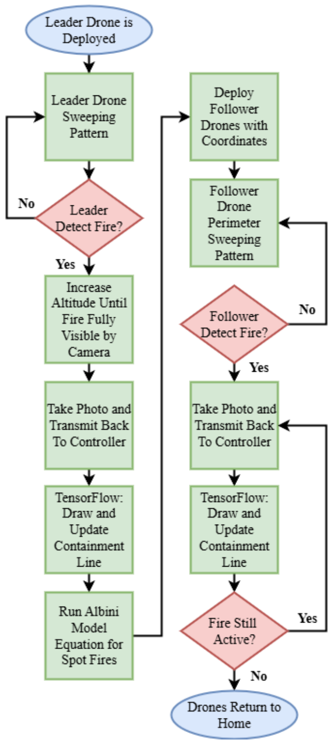

Figure 1. Flow chart showing the steps of communication between the drones and their interactions with TensorFlow

A. *Crazyflie Drones*

To provide a more complete top-down view of a wildfire, a collection of Crazyflie 2.1 (Bitcraze AB, Sweden) drones is utilized to grasp the full image. The Crazyflie 2.1 is an open-source quadcopter platform measuring in size of 92mm x 92mm x 29mm. The drone is equipped with the STM32F405 microcontroller (STMicroelectronics, Switzerland) as the bootloader for flight control and sensor data, and the nRF51822 system-on-chip microcontroller (Nordic Semiconductor, Norway) for radio communication to the Crazyradio Pa and power management. The Crazyradio Pa is the nRF24LU1+ microcontroller-based (Nordic Semiconductor, Norway) USB radio dongle that communicates to the drone through a radio connection established to a computer.

The drones are equipped with brand specific expansion decks to allow for additional integration and sensors to be used with the drone. The flow expansion deck v2 is utilized to give the drone the ability to understand movement and positioning. The VL531L1x time-of-flight sensor measures and maintains the distance from ground, while the PMW3901 optical sensor measures movement in relation to the measurements taken by the time-of-flight sensor. The multi-ranger expansion deck has five time-of-flight sensors for measuring along the drone's axes. With precision up to four meters in all five directions, it gives the ability for the drone to detect objects around it and relay the information gathered to the flow expansion deck.

Additionally, a breakout expansion deck is utilized to connect the drone to a MLX90640 infrared sensor (Melexis NV, Belgium). The breakout expansion deck allows for new hardware to be incorporated into the drones without the need for soldering, allowing for multiple integrations and hardware to be used. The MLX90640 infrared sensor has a 110° x 70° field of view, which contains a resolution of 32 x 24 pixels, totaling 768 pixels included in each image captured. Each pixel represents temperature values represented through the data captured by the sensor and a temperature range of seven meters, the further the sensor is from the surface the larger the area is covered, resulting in a larger area represented by each pixel.

Figure 2. Fully assembled drone with expansion deck sensors and thermal sensors attached.

The data collection process is initiated by the autonomous flight of the Crazyflie 2.1 drones. The flight path is a programmed search pattern designed to cover the entire area where a potential wildfire could be, based on an input GPS location. The drone searches for the simulated heat source among the high contrast pattern that simulates the terrain. Once the heat source is located the amplitude of the drone is increased to capture a complete thermal image.

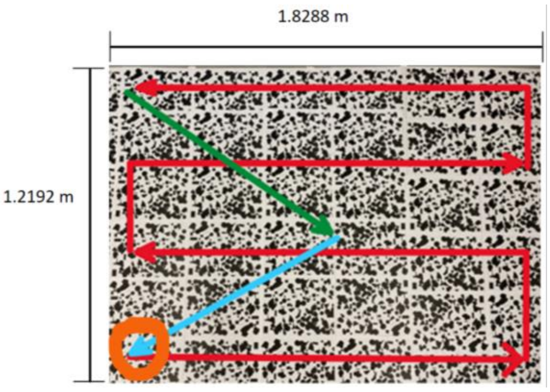

Figure 3. Designated flight path on the high-contrast pattern (simulated terrain)

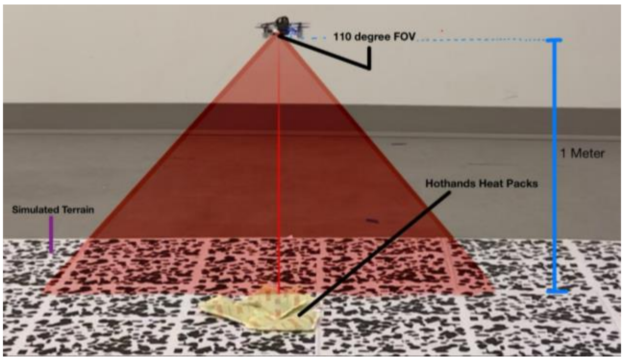

Figure 4. Diagram showing drones finding simulated heat source (*HotHands* heat packs) and field of view (FOV)

The 110° FOV allows for the capturing of photos at different angels and peripherals. This results in the drone having the ability to capture the fire in its entirety, even if not directly over the fire, which can prove crucial in real world applications.

The simulated terrain is approximately 1.8288 meters x 1.2192 meters. It takes one Crazyflie drone hovering 1 meter above the ground, approximately 30-35 seconds to travel from the designated 'home' point (the orange circle) through the designated flight path, and to return to the 'home' point. The drone travels approximately 0.5 meters per second with a slight delay occurring when turning due to the limitations present in some of the onboard sensors. This is discussed further in the results section.

B. *CfClient Program and Controller*

To allow for initial connection to the drone and the ability to gather foundational information and data for later development, the Crazyflie 2.1 native client CfClient was utilized. The CfClient allows for initialization to the drone and the ability to assign radio addresses, something that is crucial to determine which radio frequency the individual drones are operating on. The client provides software packages and specific graphs for the initialization of the expansion decks, as well as gathering the preliminary data values necessary for further development, specifically the position, flight amplitude, and the effect of flight on different expansion deck values.

C. *TensorFlow Machine Learning Model*

The objective of the TensorFlow program model is to be able to analyze thermal data obtained from the MLX90640 thermal camera attached to the Crazyflie 2.1 drones. The model is created using the keras API within TensorFlow and is trained using a collection of images captured through the MLX90640 that contain or are absent of heat signatures.

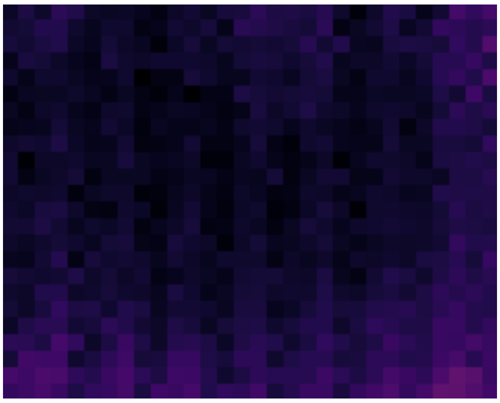

Figure 5. No fire present; training image for TensorFlow model

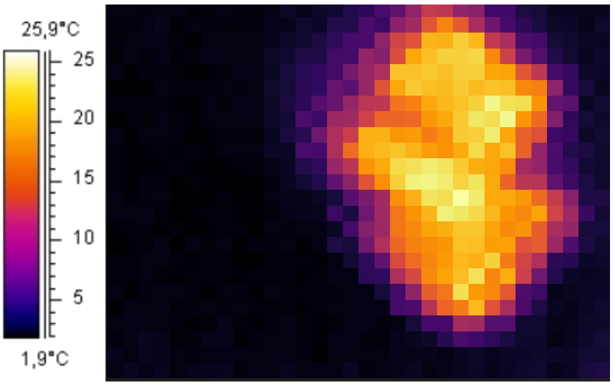

Figure 6. Thermal Scale (left); Fire present; training image for TensorFlow model (right)

After the model is trained, it is now able to be incorporated into the Crazyflie 2.1 drones. First, the drones capture an image of the entirety of the fire. For simulation purposes, the fire is simulated using *HotHands* handwarmers to get accurate and contained heat signatures (previously shown in Fig 4). This image is then remotely relayed to the TensorFlow model. This image is processed, to determine if the wildfire is present. If true, the model creates a bounding box surrounding the entirety of the fire as seen in Fig. 7.

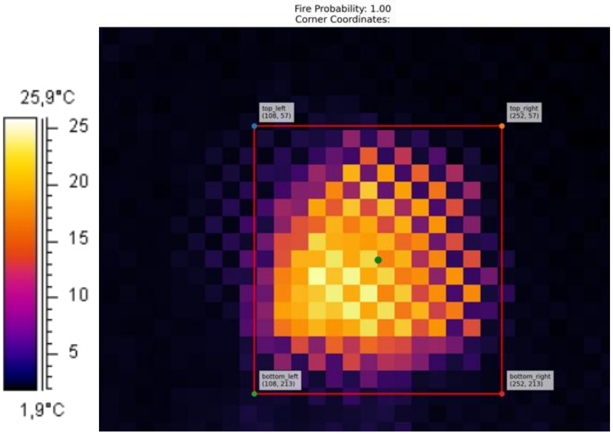

Figure 7. Thermal scale (left); Image captured from MLX90640 that is uploaded to TensorFlow model with bounding box created around the heat signature (right)

The bounding box equation is designed by changing the image from RGB into a greyscale image. This greyscale image is then compared to the values of the thermal scale, which have also been converted to greyscale. The desired color value of ’50’ was set as the minimum which is any heat signature above the dark purple color to be included in the bounding box.

The values for the corners of the bounding box are calculated through the model and stored as an array value. The center of the bounding box is then found through the arithmetic mean equation, where the mean of one of the vertical lines of the bounding box is found for the y-coordinate and the mean of one of the horizontal lines is found for the x-coordinate. These coordinates are then the respective x and y values of the center point of the bounding box. After determining the center of the bounding box, the model then runs the Albini model-based equation, which determines the most likely distance from the ‘main’ wildfire where spot fires are most likely to occur.

$$D = V_w + t_{fall} + D_{loft} \qquad (1)$$

Where D is the spotting distance from the main wildfire, V_w is the wind speed at the height of ignition, t_{fall} is the time it takes the incendiary to drop, and D_{loft} is the distance gained by the incendiary being lifted by convection. The wind speed can be determined through local weather data, while the time for the incendiary to drop and distance gained by the incendiary is typically determined through the Ember Spot Probability method. This method is commonly used by fire analysts who then input these methods into programs such as FARSITE which utilizes the Albini model to calculate spotting distance from the main wildfire. For the purposes of this experiment, it is assumed that a fire analyst would be calculating the D_{loft} and t_{fall} variable as is current protocol for calculations of spotting distance [8].

After the equation is run, the bounding box is then extended by this distance from the corners and midpoints of the box, thus creating the containment lines by connecting these points.

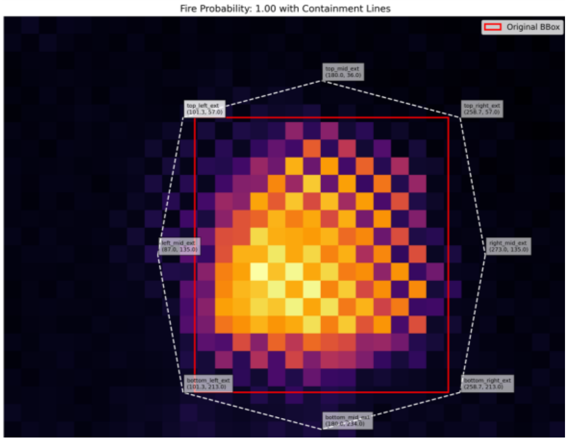

Figure 8. Original containment line drawing resulting from Albini eqaution with spotting distance value of 50

The coordinates of the original containment line are transmitted to the ‘follower’ drones which then search for spot fires in these coordinates. If a new spot fire is found, the model runs again, combines the images together, and updates the containment line drawing to now include the spot fire.

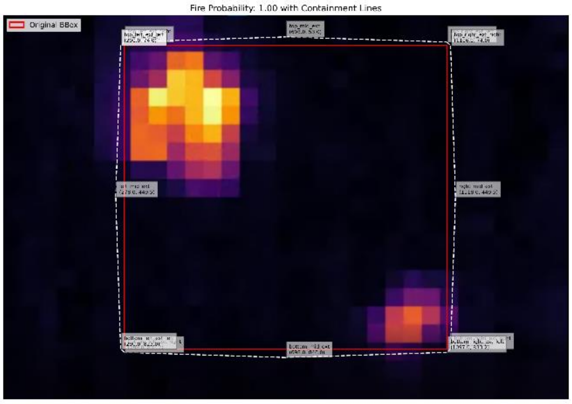

Figure 9. Updated containment line drawing from a spotfire being detected by a ‘follower’drone

III. RESULTS AND DISCUSSION

Each drone was initialized with its own unique radio address to allow for individual and simultaneous connection. Then, the drones were able to communicate and transmit data back through the Crazyradio Pa dongle connected to a computer. Through the execution of a python script, the leader drone can accurately circle in search of a fire, and once a heat signature is detected, hover while increasing amplitude from the ground until there is a ‘cold’ (black) heat signature present on all sides of the image. Once this heat signature is present, a photo is taken through the MLX90640 and remotely uploaded to the TensorFlow model, where the model successfully was able to draw and update containment lines as necessary.

In respect to the autonomous aspect of the swarm algorithm, the drones can successfully search for the fire through heat signatures, search for spot fires defined with a distance calculated using the Albini model and communicate data effectively between drones and with the computer that is running the TensorFlow algorithm. There is still a slight human interaction, where a human is required to input coordinates for the drones to start the search process and to input the values of the Albini model. The summation of the variables and total spotting distance resulting from the Albini model are all done autonomously through the TensorFlow algorithm.

The goal of the project was to prove the validity of both an autonomous drone swarm algorithm, as well as certify the results of the TensorFlow algorithm and its ability to successfully draw accurate containment lines. Through experimentation, a drone speed of 0.5 meters per second resulted in the most accurate results from all the integrated sensors. It allowed ample time for both the PMW3901 optical sensor to correctly take positional measurements of all directions and for the MLX90640 thermal camera to capture and relay thermal imaging to the TensorFlow algorithm. While the MLX90640 contains a refresh rate range of 0.5 Hz to 64 Hz or approximately 2 seconds to 15.6 milliseconds, it was found that the data handling of the thermal imaging was better processed at the mean refresh rate, which proved to allow ample time for capture and relay of the images, which when sequenced together by the TensorFlow software for processing, resulted in an accurate 'video' representation without setting the camera up for video, which when experimented with resulted in significantly less quality and more processing time and power when analyzed by the TensorFlow algorithm.

The usage of minimal hardware allows for the testing of the TensorFlow software and to prove feasibility of the implementation of the design. If the high intensity of the TensorFlow model can run and communicate with minimal hardware, it can be accurately concluded that the design can be scaled up to be utilized by more industrial technology. The universal integration of the TensorFlow model proves to allow the ability to incorporate it at a large-scale operation. The main integrator of the model is the thermal images captured through the MLX90640. Thus, it allows the model to be simply adapted for large-scale integration, through the requirement of a thermal camera and the ability to wirelessly relay the images back to a host-machine with the TensorFlow model installed. Since the model calls on all image types, it allows for the integration of different types of thermal cameras and data, the only change to the code being the pixel counts/FOV of the respective camera. By proving that the model is effective with the MLX90640 which contains 768 total pixels in each image, it can be concluded that any higher resolution or FOV thermal camera allows for clearer images and results respectively. The integration of a thermal camera with greater resolution will allow for both sharper and more pinpoint results and coordinates, compared to the current resolution and pixel count which represents a larger area per pixel.

IV. CONCLUSION

To combat the ever-increasing surge of wildfires, new technology is being utilized to help curb some of the long-lasting effects. With the incorporation of the TensorFlow model, drones can successfully and efficiently update containment lines to aid firefighters in rapidly containing wildfires to prevent additional loss of life, property, and environment. Testing shows that the usage of cost-effective minimal hardware with the Crazyflie drones, expansion decks, and MLX90640 infrared camera, has resulted in the ability to gather efficient data and heat signatures to effectively communicate with the TensorFlow model. This results in the rapid creation of updating containment lines which are the main way firefighters currently tackle wildfires. The TensorFlow model allows for the rapid integration of other drones, so long as they contain their own unique radio frequency signal and a thermal or infrared camera. It can be accurately concluded through the testing that since the results are achievable on a small scale, more affordable model, that so long as there is a radio receiver and thermal camera equipment, the TensorFlow model can be correctly and accurately incorporated with more 'industrialized' and higher quality drones that can provide even greater assistance to fighting wildfires.

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