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Robotic Wildfire Detection Using Computer Vision

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Abstract

In today's world, wildfires represent a global challenge that is accelerated by climate change, which requires researchers to propose new solutions for their detection and response. This paper is an individualized development project of an AI-driven wildfire detection system that uses Bitcraze's Crazyflie drones, where Bitcraze has developed supplemental hardware like the AI deck, flow deck, and multi-ranger deck. The starting part of this project uses OpenCV-based image processing to identify potential wildfires. Currently, the implementation only looks at the use of a single drone and its capabilities, while, hopefully in the future, the work will integrate advanced AI-based object detection and autonomous swarm control for more advanced scenarios. This research, funded by ****, shows potential for compact and affordable drones in wildfire response. The early approaches show promise and practicality in the use of AI in response to wildfires.

Introduction

With the continuation of climate change, society is beginning to experience an increase in wildfires as well as an increase in intensity, threatening ecosystems and infrastructure [1]. Traditional wildfire detection methods like satellite monitoring and ground-based patrol fall into certain weaknesses like limited coverage of an area. Unmanned Aerial Vehicles (UAVs), more commonly known as drones, can be equipped with advanced technologies, like AI, as a solution to the detection and monitoring of wildfires [2]. Bitcraze's Crazyflie drones are a lightweight and modular drone system that allows the drone to be equipped with special hardware like the AI deck to enable real-time sensing and image analysis. In this research project, we develop an autonomous drone-based detection system using Crazyflie drones. In the current phase of the project, we used Open Computer Vision techniques to detect wildfires with future use cases integrating object detection models for enhancing precision. This system will hopefully act as a warning tool capable of providing live data for necessary agencies to mitigate wildfire damage, and improve safety and environmental outcomes.

Support is provided by ****, this project aligns with the mission of fostering innovation and the expansion of new technologies. The significance of this research project extends past wildfire detection and can be applicable across a range of natural disasters like floods, hurricanes, and earthquakes. This paper contains details of the methodology behind the development of the system, with preliminary results achieved, and challenges encountered during its development. We also discuss future developments and the betterment of the technology, with the integration of swarm control and AI-based navigation which can maximize effectiveness in real-world scenarios. When demonstrating the practicality of an AI system in real life, can contribute to the field of technology-based disaster management.

Background

With the large threat to ecosystems and infrastructure traditional methods are limited, with delayed detection times, restricted visibility, and limited coverage in remote areas. These challenges can exacerbate damage due to delayed response [2]. While wildfires can be scary, they have historically been an important part of many ecosystems in maintaining ecological balance by promoting new growth and reducing the accumulated vegetation. With that being said, the frequency and intensity of those wildfires have increased dramatically due to climate change and land use. The activities have caused prolonged fire seasons, increased temperatures, and drought conditions. These symptoms all culminate in an increased likelihood of wildfire [3]. Traditional wildfire techniques heavily rely upon the use of human observations and satellite imaging. Satellite systems such as MODIS (Moderate Resolution Imaging Spectroradiometer) and VIIRS (Visible Infrared Imaging Radiometer Suite) provide imaging that is invaluable to organizations, but have some key drawbacks, such as a low temporal resolution, resulting in delayed detection [4]. Ground-based systems like fire watch towers and thermal cameras only offer a localized approach in detection capabilities, being constrained by limited range and line of sight [5]. With these limitations there lies a possibility of decreasing the losses caused by human monitoring, with hopeful results with autonomous monitoring.

With the advancement of AI, it has emerged in a number of various industries as a solution to a wide range of issues, transforming the landscape of education, industry, and everyday living. The use of AI can be particularly helpful in the areas of early detection of wildfires, predicting the spread of said wildfires, and where to allocate resources. Deep learning algorithms, such as convolutional neural networks (CNNs), have been used to process satellite imagery to detect smoke and fire at a level of high precision [6]. These models are trained on extremely large datasets including images of fire allowing these models to identify fire signatures in differing environmental conditions, even if there is some obstruction by smoke and low light. Machine learning models also can contribute to the prediction of wildfire spread by analyzing meteorological data, vegetation types, and topographical information. For example, reinforcement learning algorithms have been deployed to simulate the behavior of fires, allowing fire managers to evaluate the different containment strategies [7].

In addition, AI systems are able to integrate with Internet of Things (IoT) devices, like temperature and humidity sensors, to provide live data of fire-prone areas. The integration of AI with UAVs has the ability to significantly advance wildfire detection and monitoring strategies. Drones equipped with AI-based image recognition can detect fire hot spots and provide geospatial data to responders in real time. Unlike the aforementioned satellite systems, drones are able to operate at low altitudes, which offer higher-resolution imagery and faster data acquisition [8]. Onboard processors allow drones to have AI capabilities, and allow drones to analyze images of wildfires in-flight, allowing for autonomous decision-making, and reducing reliance on centralized control. A particularly important advancement is the use of swarm intelligence, where multiple drones coordinate to cover a larger area more efficiently. Swarm algorithms are inspired by the behavior of natural systems like ant colonies and flocks of birds. The replication of natural behaviors allows for dynamic task coordination and adaptive navigation in complex environments [9].

Despite large swaths of progress in everything from drones to AI, microchips, and computer vision, there still remain certain challenges for wildfire management. Environmental factors like dense smoke and high winds can interfere with sensors onboard drones. There are also concerns with the onboard computational demands for AI processing, due to the need for both lightweight, powerful, and energy-efficient processors to maintain the feasibility of the use of drones. As always there are data security and privacy issues with surveillance, these must be addressed to ensure public acceptance and compliance with regulatory bodies. In addressing the challenges of using drones and AI, there is the ability to exponentially improve the response to wildfire management and response [10].

Methodology

To develop the autonomous wildfire detection system within the drone you have to combine different elements of hardware, software, and testing. This section will explain the nuances of combining those three elements to create the system, as well as the challenges encountered with development.

I. Hardware Architecture

The detection system relies on the ability to modify and program Bitcraze's Crazyflie drones and the associated decks to build a program that detects wildfires. The AI deck uses the Gap8 processor for the main AI onboard computations. The Gap8 processor has a multi-core architecture, where each of the eight cluster cores will independently handle threading, allowing for a simultaneous execution of commands and tasks, where in this case, it is processing an image and identifying it as a wildfire. The onboard chip does have 64 KB of shared memory, which allows for reduced latency because there is no need to access external memory during heavy computational tasks. This chip allows for different support modules like I2C, UART, and SPI for communication [11][12]. The Gap8 is an energy-efficient chip, extremely useful for drones seeing as battery level can impact the duration of flight time. The processor also has compatibility with different AI concentrations, making it useful for the task of wildfire detection.

The AI deck from Bitcraze also has an onboard camera module that captures frames in a Bayer RGB pattern, which provides raw data from vision-based tasks. The camera supports a frame rate of up to 60 FPS and has an adjustable exposure setting that allows it to adapt to different lighting [11].

The ESP32 Wi-Fi module onboard the AI deck allows for wireless communication between the drone and a base station. The Wi-Fi module has a dual-core processor, allowing for communication and the transferring of data, it is optimized for low-latency transmission, proving extremely useful in handling situations in real-time.

There are also other modular components that are a part of the Crazyflie drone like the Flow Deck, the flow deck has an optical sensor that provides positional data by detecting movement relative to the ground. Some of the key aspects of this deck are its ability to estimate the velocity of the drone as well as being able to keep the drone at a certain altitude. Another deck that is used is the Multi-Ranger deck. This deck has four optical sensors similar to the flow deck that are all placed in a square pattern that allows for the drone to implement a collision avoidance system due to the deck tracking movement in four different directions, while also making proximity-based navigation possible, especially in autonomous systems [13][14].

II. Training and Evaluation Data

To develop a wildfire detection algorithm, it's important to use the best data in order to replicate the drones need for emergent responses and can accurately represent fire in different conditions. Since the project uses OpenCV-based image processing, rather than a deep learning model, training isn't needed yet. However, a real implementation of AI-based fire detection would require the appropriate data sets.

For training data, if a machine learning model is integrated it would require a good data set that would include:

- Fire Images: A diverse set of wildfire images that include smoke, flames, and different lighting conditions.
- Non-Fire Images: Varied natural and urban environments to prevent false positives.
- Synthetic Data: Augmented images where the fire was added artificially for a more well-rounded dataset.

There are publicly available datasets like FireNet and FIRESENSE, that contain labeled wildfire images and could be used as the basis for training a model.

Evaluation data differs from the training data because it is used to test the performance of the model. This is to make sure the model can "generalize," rather than memorizing specific fire patterns. For the accurate evaluation of a model, you would need to make sure that:

- Unseen Data: The model should be tested on images that weren't used during training.
- Challenge Cases: Images that would include occludded fire, varying smoke intensity, and obstructions within the environment.
- Real-World Tests: To truly evaluate a model like this, the best way to evaluate is to actually use drone captured images and assess that way.

The difference between Training and evaluation data is to make sure that the algorithm is not memorizing certain aspects of fire but actually learning to identify fire across different scenarios. If deep learning is used in future work, certain performance metrics such as, precision, recall, and a F1-score, will be used on the evaluation dataset to measure accuracy and robustness.

III. Software Implementation

The software stack integrates the use of multiple components with the help of Python and GAP SDK tools. Python is used for the development of higher-level control algorithms, which include communicating with the Crazyflie Platform and the Crazyflie Python API. It also helps with the development of the fire detection and tracking algorithm using OpenCV, where using that data you can build a visualization with Dash and Plotly libraries. With the GAP SDK for the Gap8 processor, it facilitates the deployment of models to the processor allowing for AI models that are trained on TensorFlow to be exported to the chip[15]. While Linux is used for firmware compilation, Windows is used for debugging and visualizing what is happening with the program.

OpenCV is an open-source software library that provides tools for computer vision and machine learning. This toolbox enables us to use drones and AI to automatically detect wildfires. With OpenCV that are certain detection methods, one of them being color segmentation. Color Segmentation uses HSV color space to isolate fire like colors, masks are then created for each color (like red, orange, and yellow) and then combined to highlight what represents a wildfire. OpenCV also uses contour analysis, which allows for data to be filtered based on area and consistency to eliminate noise and things that are non-representative of fire [16]. An additional aspect of detection is dynamic calibration, where HSC thresholds can change based on the drone's onboard light sensors to adapt to the needs called in varying environmental scenarios.

Results

The results of this project show a successful implementation of a wildfire detection system using the Crazyflie drone integrating OpenCV computer vision techniques. With the implementation of these systems, you can use OpenCV to process live video frames from the drone's camera identifying regions that match the predetermined HSV thresholds set in the algorithm, identifying the reds, oranges, and yellows. The algorithm successfully detects and highlights these regions by drawing boundaries around the areas where the algorithm detects a "wildfire." Additionally, the size and location of these regions are analyzed to estimate the space where the wildfire is contained and then used to generate spatial coordinates (x,y,z) relative to the drone.

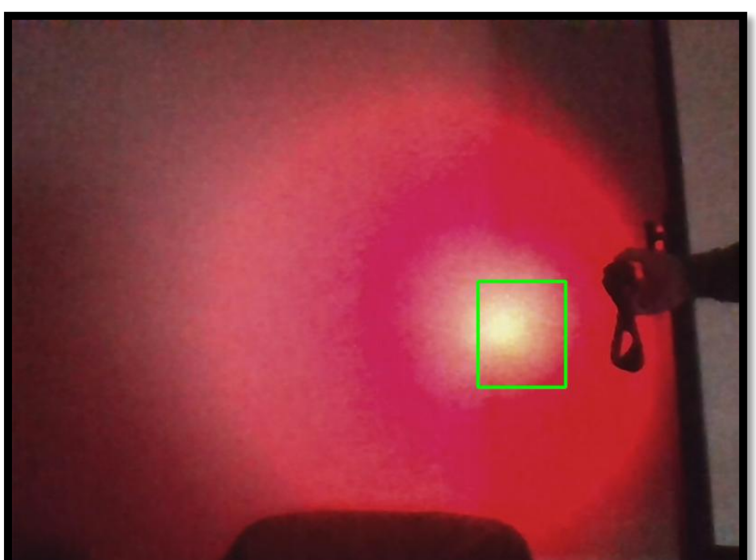

Figure 1

Figure 1 shows a sample output from the fire detection algorithm, where a simulated fire source (a red RGB LED) is detected. The region of the fire is detected and bound by a green box, and then the area and depth are calculated based on the image. Although, as you can see, this algorithm mostly focuses on the brightest part of the LED, showcasing the work that needs to be done, but overall this shows the system's ability to process frames in real time to identify wildfires.

In addition to detecting wildfire, this algorithm can map the trajectory using the real-time video feed. Using Python's Dash and Plotly libraries, the system updates regularly a 3D scatter plot displaying the x, y, and z coordinates of the detected fire. The visualization can provide a useful and comprehensive view of the fire's movement through space, relative to the drone, which can assist in the monitoring of wildfire spread.

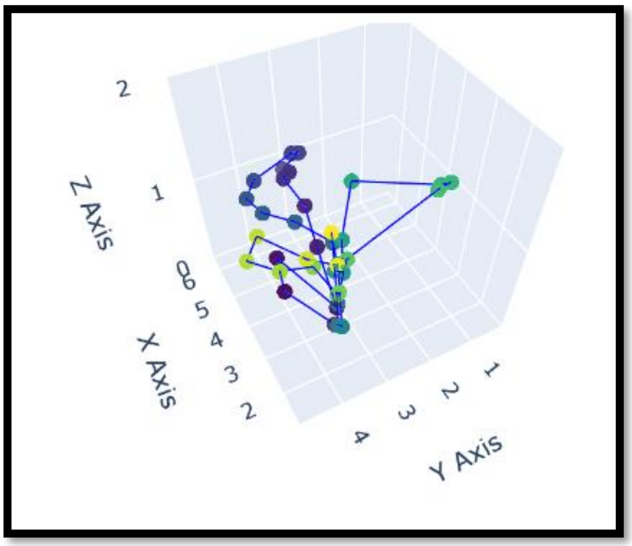

Figure 2

Figure 2 illustrates the 3D trajectory of the detect object during a test. The plot highlights the objects path over time, where markers are induction the changes in position. The gradient color is used to distinguish changes in time, which can show the behavior of the fire. While this is a promising start, Figure 2 only displays the movement of the fire in a 2D space when a more accurate display would be a 3D plot. With the betterment of the project, eventually adding depth cameras will allow for the ability to plot the full wildfire in the 3D dimension.

Preliminary testing in a controlled environment suggests that the algorithm can correctly identify the so called "wildfire" almost every time, but not tested a enough times to be statistically significant. The latency of the algorithm is slightly high when compared to modern systems, with a noticeable amount of lag, but still fast enough to detect wildfires in real time. With plotting, the Dash visualization updated very fast showing the real time data of the system trajectory of the simulated wildfire.

I. Figure 1: Sample output of the fire detection algorithm detecting the fire region.
II. Figure 2: Interactive 3D plot using Dash showing the trajectory of wildfire.

The early results of this project show a real promise in the use of lightweight drones in the autonomous response and monitoring of wildfires. During the next phase of the project will hopefully address some of the accuracy of the wildfire detection processing, proper mapping in a 3D environment, and the use of swarm control.

Challenges

During this project there have been a number of different challenges while developing the system. Namely, the depth and 3d mapping poses a real challenge when the AI deck camera may have trouble with depth, necessitating a use swarm control, where 2 or more cameras can possibly detect the 3rd dimension of space. Also, in an environment where there is wildfire, the conditions would pose as less than ideal due the the level of light and amount of smoke in the air around the fire. If the system is resilient to more life-like conditions, it could potentially be a clear-cut solution in the monitory of wildfires. Computational constraints of the Crazyflie drones could also prove as a limitation in large scale projects due to more complex algorithms requiring more power affecting the overall drone's performance. The biggest challenge is the current implementation of the algorithm, where a real-world scenario would be much rougher on the drone and could possibly mess with the entire system.

Future Plans

Hopefully, with the completion of the algorithm and successful testing, we can implement swarm control. Swarm control involves the coordination of multiple drones to work together, increasing the system's coverage of an area. To achieve these goals future work will involve the development of systems for drone-to-drone communication, optimizing swarm algorithms, to provide a scalable and efficient solution for the detection of wildfires on the monitoring of said wildfires.

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