Autonomous Drone for Dynamic Smoke Plume Tracking

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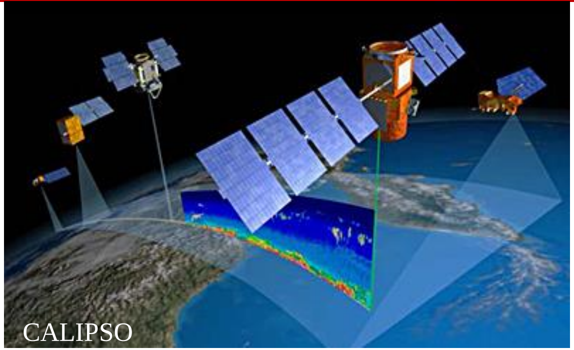
Introduction

Importance of Understanding Particle Transport in the Atmosphere




- **Significance of atmospheric particle transport: Implications for environment monitoring, climate modeling, and impact on human health** (Kumar et al. 2011, Kok et al. 2012, Evangeliou et al. 2020)
  - Smoke plume from forest fires (Jaffe et al. 2020)
  - Volcanic ash during eruptions (Butwin et al. 2015)
  - Movement of sand, dust or snow (Dentoni et al. 2022, Mott et al. 2010)
- **Particle transport in the atmosphere covers a constantly evolving broad range of scale**
  - Particles measuring micrometers to events spanning beyond kilometer scales (Sokolik 2019)
  - Particles' morphology and composition critically affect particle settling and dispersion (Lahde 2013)
- **Significant gap remains in field data measurement capabilities**
  - **Challenge: Develop tools to measure both large-scale motion + individual particle details**

Existing Characterization Tools



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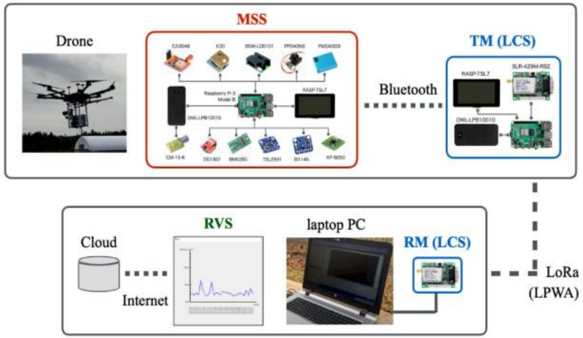
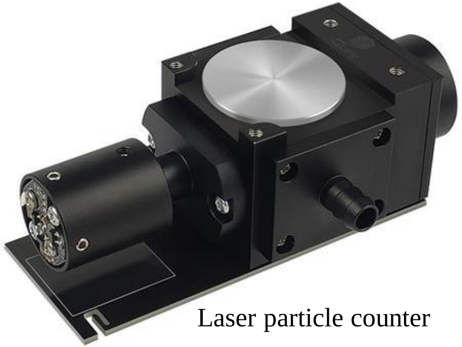
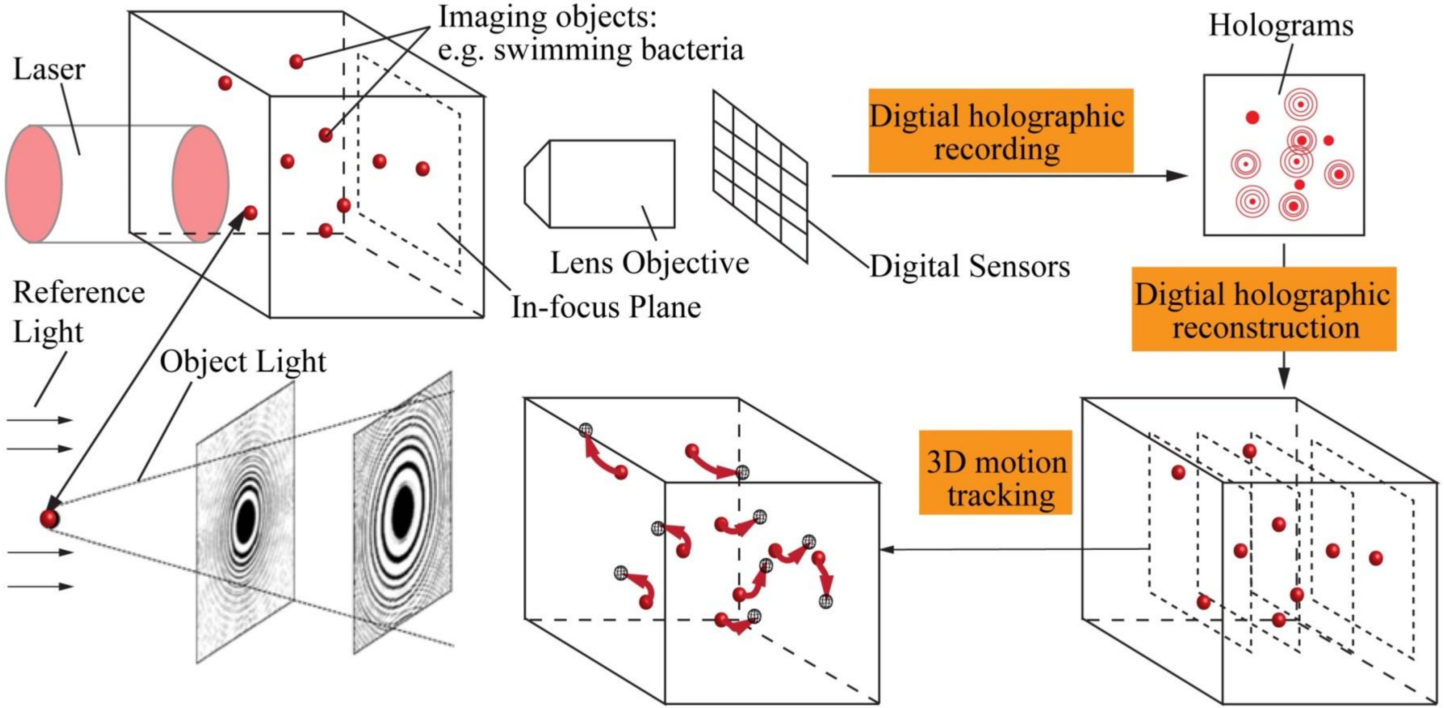




Laser particle counter

- **LiDAR-based remote sensing devices:**
  - Uses satellites with LiDAR array to measure particle events on large scale in the scale of continents (Cloud Aerosol Lidar & Infrared Pathfinder Satellite Observation by NASA, Wandinger et al. 2005, Sokolik et al. 2019)
  - Limitations: Unable to capture detailed particle information, such as changes in individual particle concentration and spatial distributions
- **In –situ particle measurements tools:**
  - Analysis with PM sensors (Madokoro et al., 2021), optical particle counters (Hagan et al., 2020) and aerodynamic particle analyzers (Johnson et al., 2018) using light scattering and aerodynamic properties to detect particle size and distribution.
  - Limitations: Measures only bulk properties like concentration of aerosols; individual particle size and morphology have to be assumed (Grimm et al. 2009)

Digital Inline Holography (DIH)

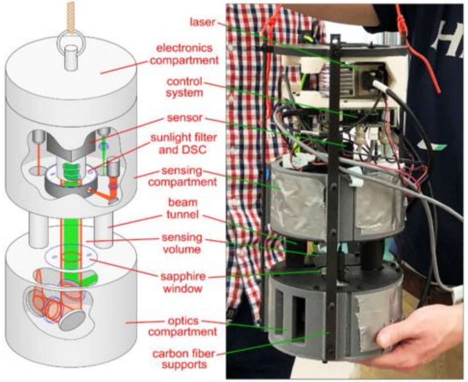


- **Emerging**, **low-cost**, **compact**, method of particle characterization (Katz et al. 2010, Berg et al. 2022)
- Advantages**: Label free** characterization with a **large depth of field**
- Information beyond morphology: Phase information including **3D location and refractive index**

Existing Characterization Tools (based on DIH)

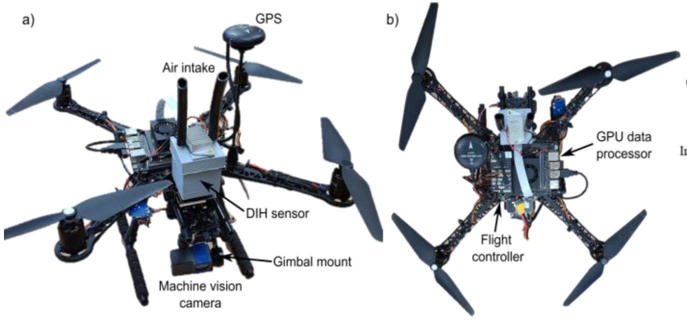
- **Holographic Detector of Clouds (Beals et al., 2015)**
  - DIH attached under aircraft wing
  - Uses DIH for studying cloud composition (water and ice) and capture spatial structure, droplet size distribution
  - Limitations:
    - Not able to fly close to surface for sample collection
    - Not suited for detailed scanning of small area
    - Data collection is expensive

- **UAV based Digital Inline Holography (Kemppinen et al., 2020)**
  - Heavy payload of DIH with tethered connection
  - Manually controlled flight for sample collection
  - Limitations:
    - System not autonomous
    - Limited mobility with sensor attached to rope
    - Unable to track or monitor the dynamic changes in particle properties

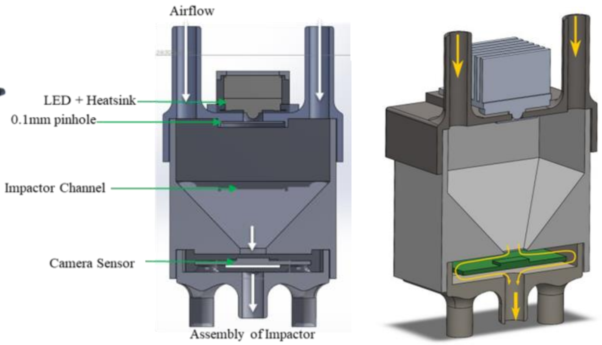


Kemppinen et al., 2021

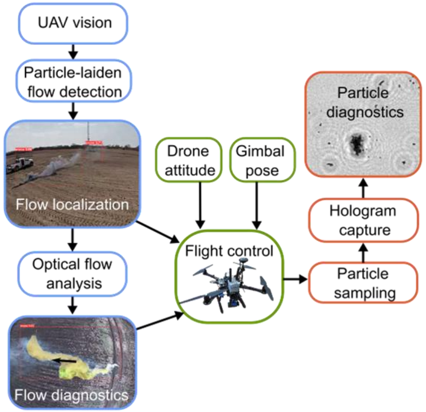
Bristow et al., 2023: Autonomous Aerosol Diagnostics with UAV



Hardware



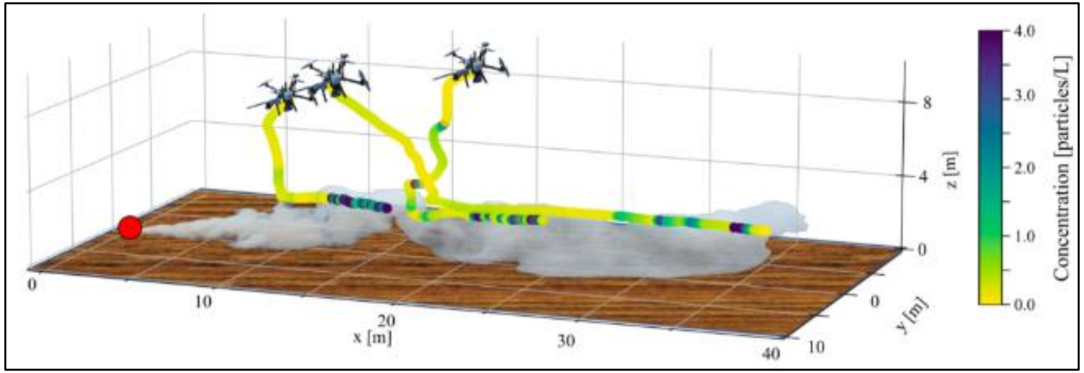
DIH sensor overview and Images



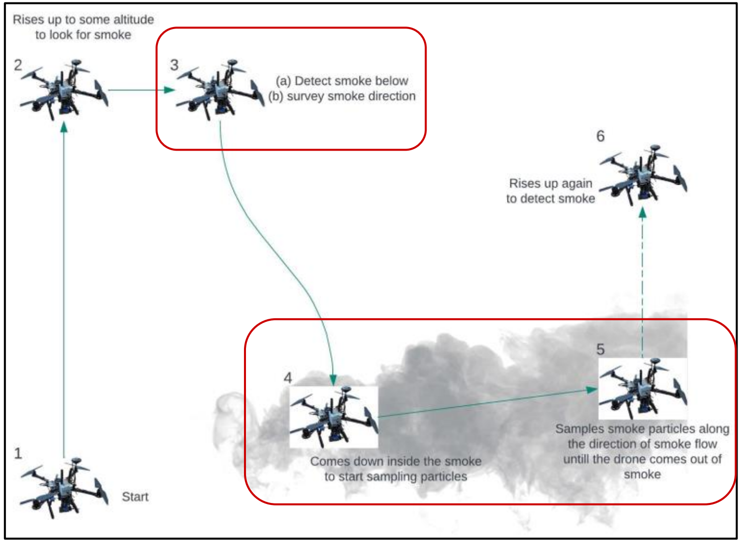
Bristow et al., (2023) Smoke Sampling Algorithm

- **Atmospheric Aerosol Diagnostics with UAV-based Holographic Imaging and Computer Vision (Bristow et al., 2023):**
  - Drone-based system: Advantages in **Flexibility and mobility**
  - Equipped with DIH: Compact DIH provides **real-time high resolution holographic images**
  - Autonomous system: **Deep learning-based computer vision algorithms** helps to detect and follow particle laden flows autonomously
  - Mobile measurements: Drones can **effectively navigate** through particle laden flow, such as smoke

Bristow et al., 2023: Autonomous Aerosol Diagnostics with UAV



Particle diagnostics data from autonomous flight, showing a spatial map of particle concentration along the UAV path, moving along heading estimated by optical flow

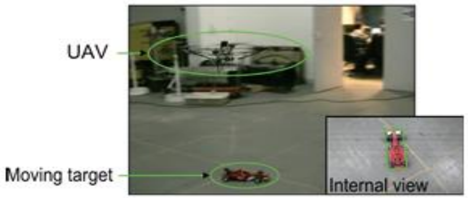


Overview of the Bristow's smoke sampling algorithm

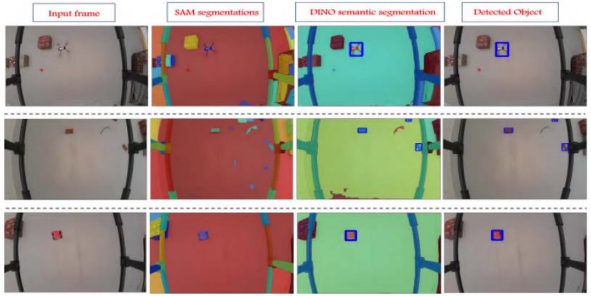
- **Limitations of Bristow et al. (2023):**
  - **Lack of direction adaptation in realistic smoke scenarios with rapidly changing wind directions and turbulent environment:** Absence of feedback from within the smoke; in case of smoke changing direction due to wind, the system fails to detect when drone comes out of smoke and how to maneuver back in
- **Objective: Enhance real-time smoke tracking capabilities for dynamic particle dispersion**

Related Works

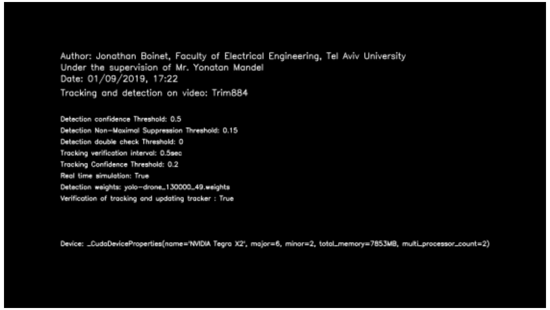
Detection and Tracking in Drones



Drone tracking small vehicle



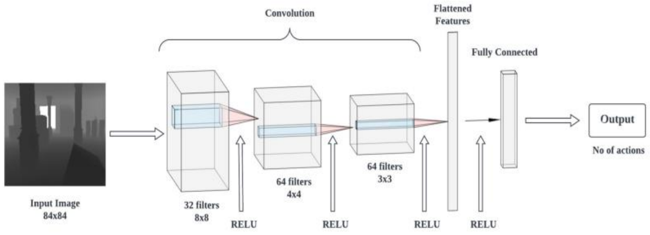
Detection scheme for detecting Drones, Bricks, and RC Cars.

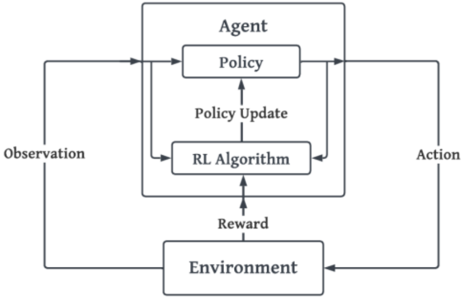


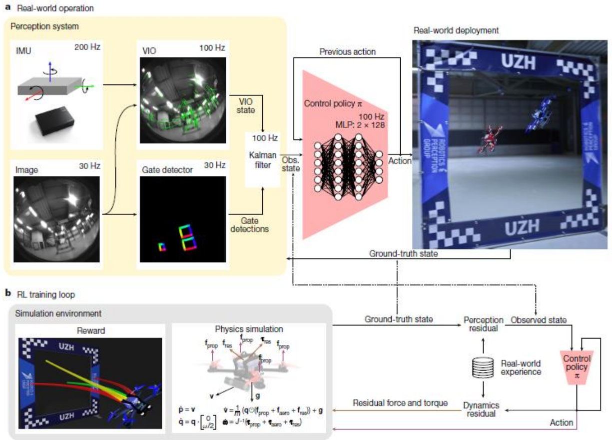
Drone tracking drone using YOLO and GOTURN on Nvidia Jetson TX2

- **Real-time vision-based target object detection and following**:
  - Target object detection using traditional image processing (Teuliere et al., 2011; Malouf et al., 2024) or deep learning approaches (Kanellakis et al., 2017; Ramchandran et al., 2021; Zaldi et al., 2022)
  - Tracking maneuvers are then executed using PID controllers (Malouf et al., 2024) often coupled with Kalman filtering (Barisic et al., 2019) to address uncertainties.
  - Limitations in context of our objective:
    - Atmospheric particle transport, such as smoke plumes, is fluid and dynamic, differing significantly from the more predictable objects typically tracked by drones (Teuliere et al., 2011; Malouf et al., 2024; Cesetti et al., 2009)
    - Current systems are more optimized for performing in controlled environments

Deep Reinforcement Learning for Drone Control







- **Deep Reinforcement Learning for Vision-Based Navigation in Drones:**
  - Enhanced adaptability and robustness in dynamic and unpredictable environments (Aburaya et al., 2024)
  - Methods include vision and depth-based localization and navigation, that are primarily applied to object avoidance, tracking, and drone racing scenarios (Kaufmann et al., 2023, Ma et al., 2023; Zhou et al., 2019)
  - Limitations in context of our objective:
    - No prior research focused specifically on using these methods to track and follow atmospheric flows, such as smoke plumes using drones

Related Works

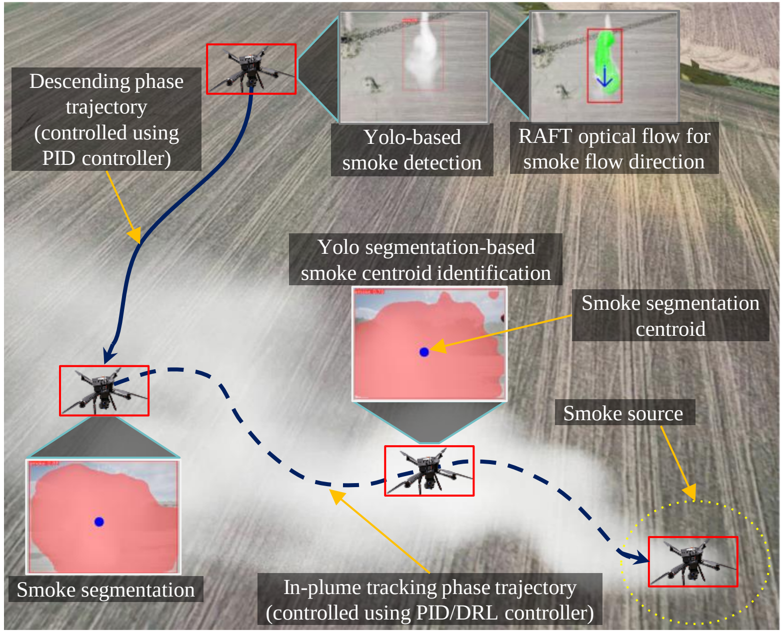
- **Summary:**
  - **No existing research specifically focused on utilization of drones for tracking atmospheric particle transport such as smoke plumes.**
  - Relevant studies in this field have primarily concentrated on employing drones to track more predictable static or dynamic objects such as vehicles, people, or other drones
  - Drones typically use PID controllers to maintain their position relative to a target object.
  - **Challenges with Irregular Objects:** For tracking smoke, segmentation methods are more effective than bounding boxes.

- **Challenges in Tracking atmospheric flows:**
  - **Target Object:** Atmospheric flows like ‘smoke plume’
  - **Nature of Smoke Plumes:** Unlike solid objects, smoke plumes are fluid and dynamic.
  - **Constant Evolution:** Systems must adapt to the changing shapes and densities of smoke.
  - **External Conditions:** Factors like wind and turbulence require advanced tracking methods.
  - **Resource Constraints:** Efficient algorithms are needed to process data in real-time with limited onboard resources.

Methodology

Overview

- **Initial Smoke Detection and Descending Phase:** Begins by autonomously positioning the drone above the smoke plume, capturing a top-down view. Once smoke is detected, the drone descends to the smoke dispersion region
- **Smoke Tracking Phase:** Continuous segmentation of smoke within the camera frame and calculating the centroid of the segment to find the centroid of the densest region of the smoke
- **PID Controller for Smoke Tracking**: Commands the drone to adjust its position based on the error between the camera's center and the smoke centroid, enabling effective tracking even when smoke shifts

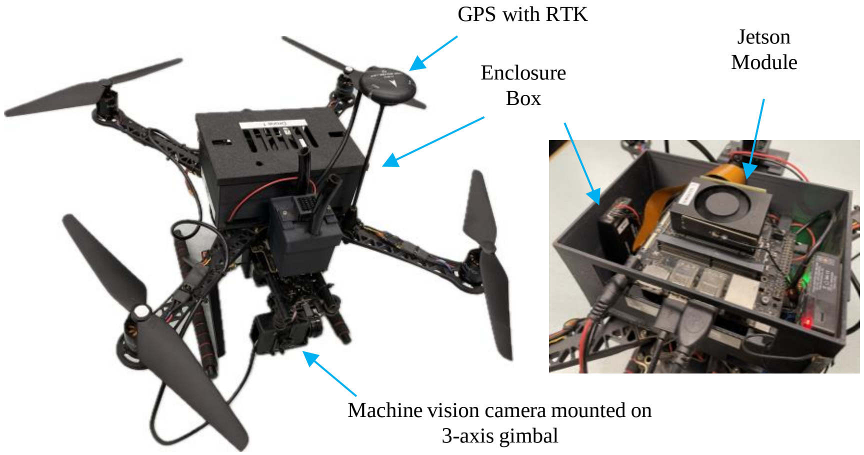


Autonomous drone-based smoke tracking system working principle

- **DRL Controller for Smoke Tracking:** Utilizes PPO algorithm, trained in a simulation. The DRL policy network predicts the drone's motion based on segmented images, aiming to guide the drone towards areas of higher concentration when smoke shifts due to wind changing direction

Hardware

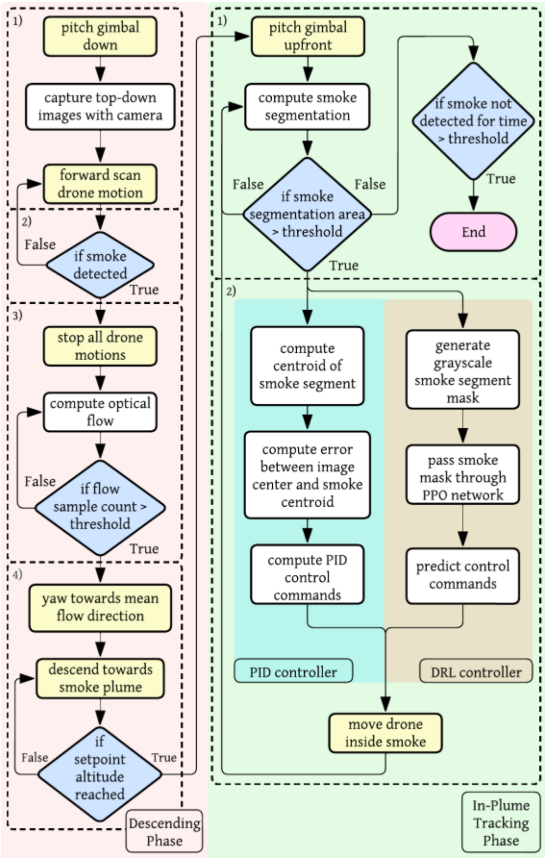
- **Upgrades on the Bristow et al., 2023 hardware setup:**
  - **Pixhawk**: Onboard flight controller, firmware updated to latest version 4.5.2
  - **GPS with RTK setup:** Connection established with a ground-based RTK station for more precise GPS location.
  - **Machine vision camera:** GoPro replaced with **ArduCam 12MP USB camera** to reduce latency while maintaining image quality for flow measurements and segmentation.



Autonomous drone-based smoke tracking system hardware

  - **Onboard GPU:** Updated from Nvidia Jetson Xavier NX to **Nvidia Jetson Orin Nano** for onboard edge-computing with high-efficient inference time **booting from NVMe SSD.**
  - **Enclosure Box with more efficient wire management:** Newly designed 3D printed enclosure box for enclosing all the wires, cables Orin, power distribution board, receiver-transmitter modules, etc.
  - **Battery Holder:** Newly designed 3D printed battery holder for stabilized flight as it maneuver through smoke plume.

Algorithm and Software Architecture

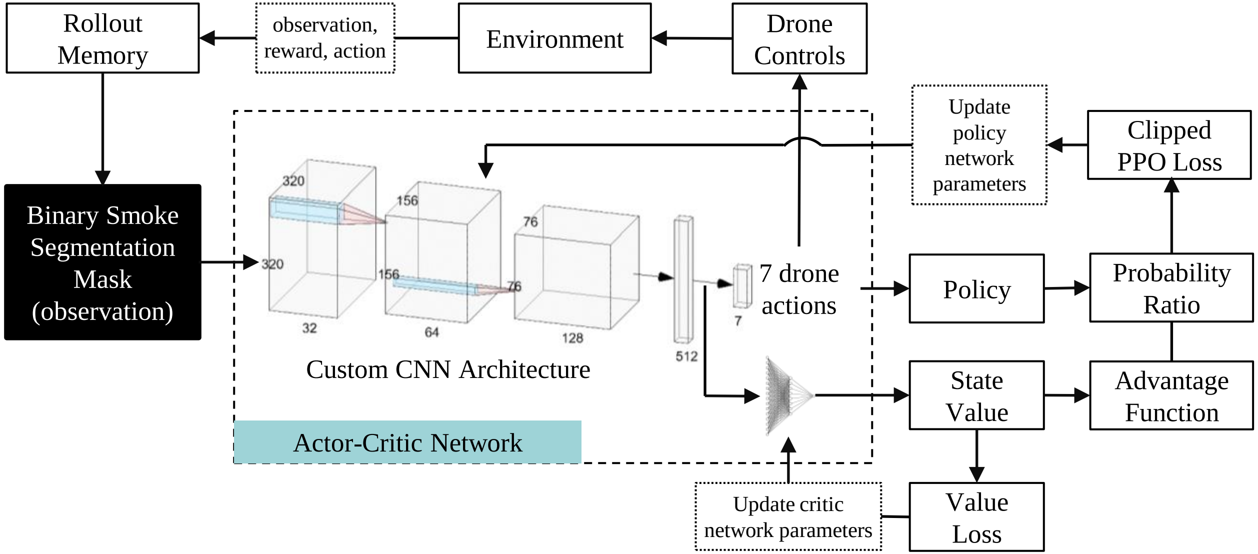


The framework of the autonomous drone operation algorithm

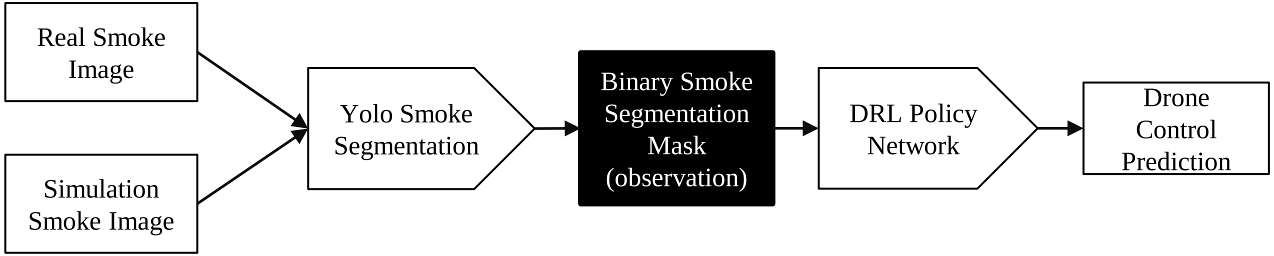
- **Descending Phase:**
  - **Hovering & Smoke Detection Setup:** Drone hovers above the plume; gimbal set for top-down view.
  - **Smoke Detection:** YOLO detects smoke in top-down images
  - **Optical Flow Analysis:** RAFT Optical Flow computes smoke direction using bounding box from the detection.
  - **Yaw Alignment & Descent:** Drone aligns with smoke flow; PID controller used for descent within the plume dispersion region.
- **In-Plume Tracking Phase:**
  - **Smoke Segmentation:** YOLOv8-seg identifies and segments dense smoke regions; centroid calculated for tracking.
  - **Drone Trajectory Control:**
    - **PID Controller:** Corrects drone's position based on location of the smoke segments centroid in the camera frame.
    - **DRL Controller:** Inputs binary smoke segmentation mask to predict drone movements towards smoke and maximize return.
    - **Controller Switching:** If required, current system allows operator-controlled switching between PID-DRL controls.

DRL Drone Control: Proximal Policy Optimization (PPO)

Segmentation and PPO-based Architecture (training) :



Inference and Sim2Real Transfer :



Simulation Assessment

Simulation Environment

- **Challenges of Developing Autonomous Drones**
  - Testing - Requires access to a large open space as a safe testing zone
  - Safety Concerns - Drones could behave unexpectedly while testing
  - Resources - Failures and crashes could result in large expenses for repairs
  - External Factors - Testing and deployment depends heavily on weather conditions (wind, rain, snow)

- **Simulation in Unreal Engine 5.1.1 (UE 5.1.1) makes up for these challenges:**
  - Supports **rapid algorithm development and testing**
  - **Evaluate algorithm** prior to actual deployment
  - **Train DRL-based PPO controller**
  - **Evaluate algorithm** in different test smoke (wind) scenarios

Simulation Environment in UE 5.1.1

Simulation Environment

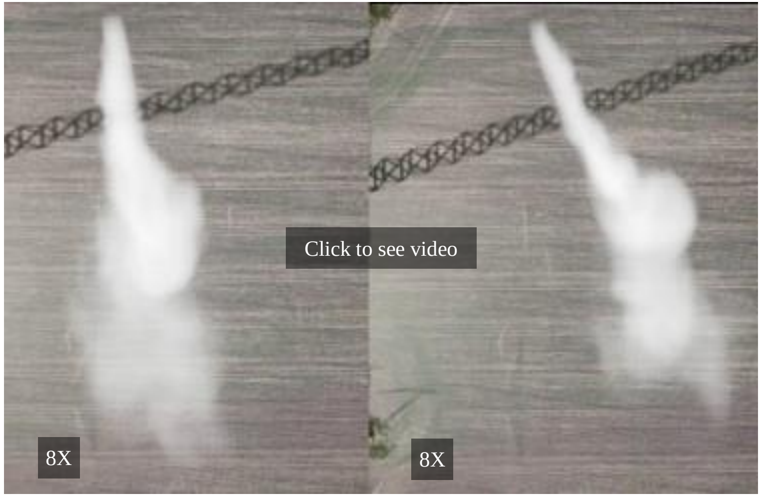
Actual photo of Eolos site at UMore Park

Recreated Environment in UE 5.1.1

- **Simulating Eolos Environment**
  - Usual location of field deployment and testing: The **Eolos Wind Energy Research Consortium** at UMore Park in Rosemount, Minnesota
  - **Environment created in UE 5.1.1** to keep the simulation as close to reality as possible
  - Main components: Clipper Liberty Wind Turbine and a 130-meter-tall Meteorological Tower
  - Blender was utilized for designing both the Met-Tower and Wind Turbine, while the map was reconstructed through the capture of 3D imagery using Google Earth's vision camera.
  - The designs were finally imported into UE 5.1.1 and foliage is added to the environment

Realistic Smoke Simulation

Simulated black and white smoke in Unreal Engine

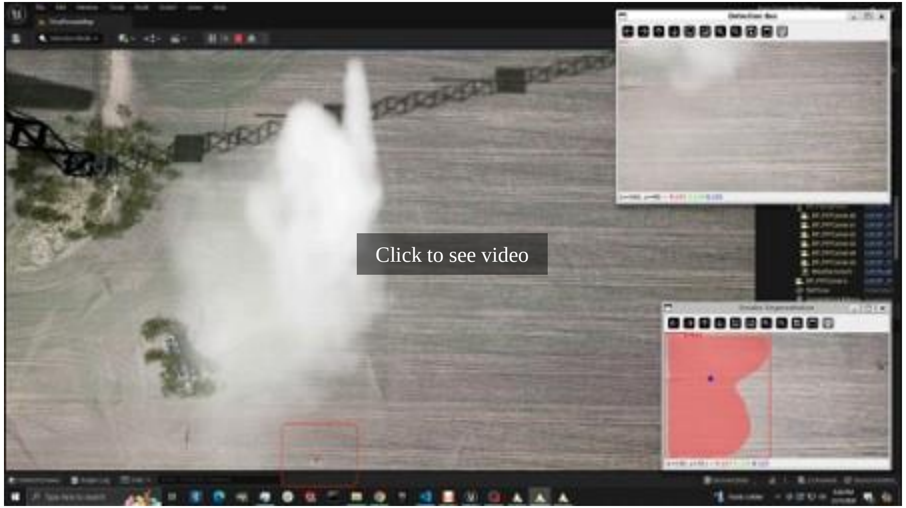


(a) Steady unidirectional Smoke flow (b) Unsteady Smoke Flow with High-Frequency Horizontal Fluctuation

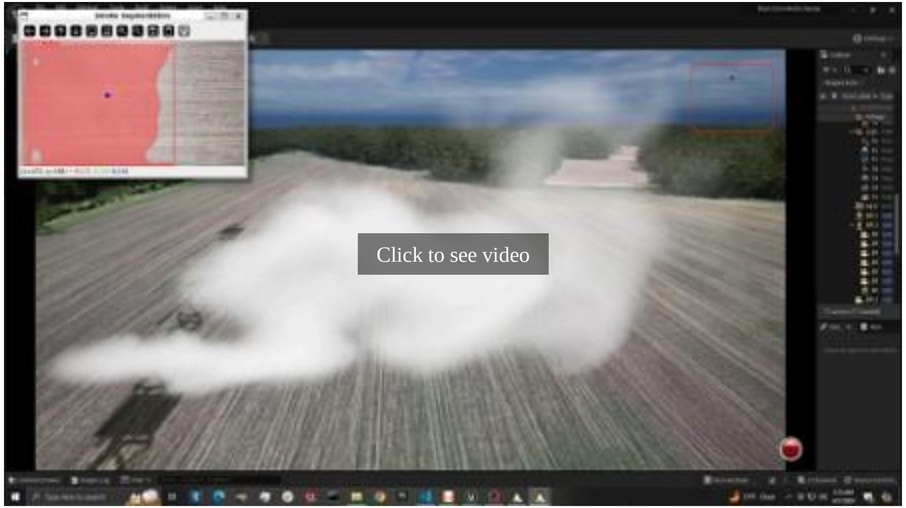
DRL training in Unreal Engine simulation

- **Simulating smoke with controlled wind**
  - Smoke is simulated using Niagara Plugin in Unreal Engine 5.1.1 (with Niagara, Niagara Fluids, Chaos Niagara and Niagara Custom Data Interface)
  - The speed and direction of smoke flow needs to be controlled for algorithm testing. This was done by creating a blueprint in the event graph which controls the wind speed and direction.
  - **DRL was trained for 5 hours covering 1 million timesteps**. The smoke conditions alternated between steady, unidirectional and unsteady, high-frequency fluctuation flows.

Smoke Tracking : PID Controller



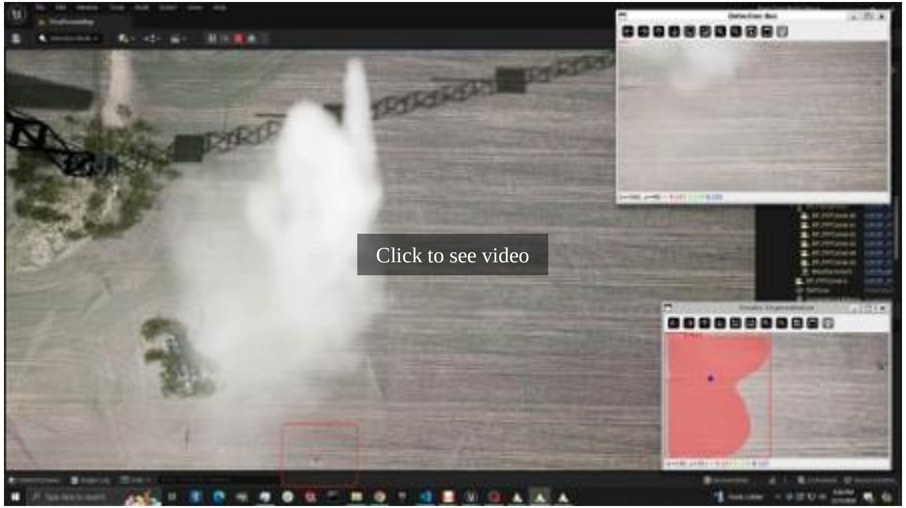
Drone autonomously tracking smoke using PID (top view)
[red bounding box shows the drone location within smoke]



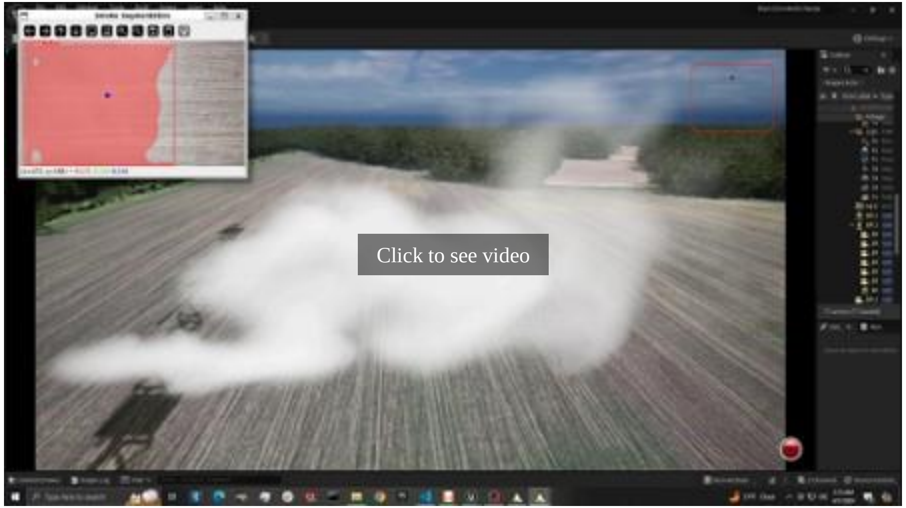
Drone autonomously tracking smoke using PID (side view)
[red bounding box shows the drone location within smoke]

- **Autonomous smoke tacking using drone simulation:**
  - Smoke segmentation and detection using yolov8
  - Drone controlled using PID controller based on the positional error of the segmentation centroid
  - Simulation demonstrates the process of drone entering the smoke, tracking the smoke along its flow path, and ultimately reaching the source of the smoke using PID controls.

Smoke Tracking : DRL Controller



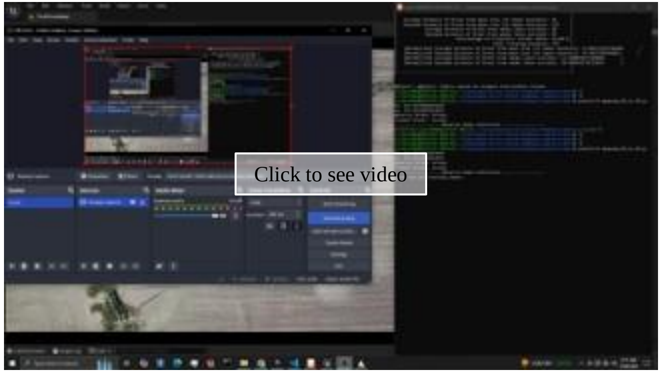
Drone autonomously tracking smoke using DRL (top view)
[red bounding box shows the drone location within smoke]

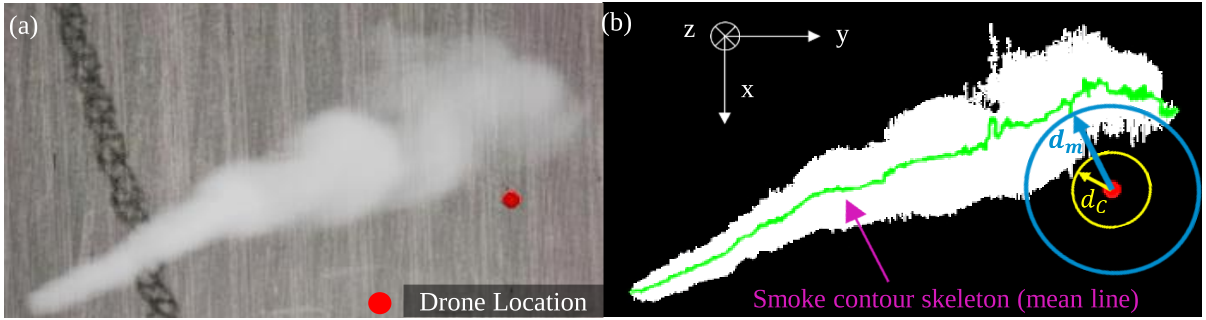


Drone autonomously tracking smoke using DRL (side view)
[red bounding box shows the drone location within smoke]

- **Autonomous smoke tacking using drone simulation:**
  - Smoke segmentation and detection using yolov8
  - Drone controlled using smoke-segmentation and trained PPO-based DRL controller
  - Simulation demonstrates the process of drone entering the smoke, tracking the smoke along its flow path, and ultimately reaching the source of the smoke using DRL controls.

Smoke Tracking Evaluation





Smoke Tracking Evaluation (in smoke flow changing direction)

- **Smoke tracking evaluation:**
  - Tracker drone location projected in the top-down view of smoke using RANSAC
  - The smoke contour is detected, and the mean line (skeleton) is calculated from it.
- **Five metrics used for performance evaluation:**
  - Normalized average distance of the drone from the mean line $\tilde{\mu}_m = mean(d_m)/L_{ref}$
  - Normalized maximum distance of the drone from the mean line $\tilde{d}_{m,max} = (d_m)/L_{ref}$
  - Normalized average distance when outside the smoke plume $\tilde{\mu}_c = mean(d_c)/L_{ref}$
  - Normalized maximum distance when outside the smoke plume $\tilde{d}_{c,max} = (d_c)/L_{ref}$
  - Percentage of time inside the smoke plume $\tilde{t}_R$ (L_{ref} is the total smoke tracking length)

Smoke Tracking Evaluation

- **Smoke tracking evaluation:**
  - Tracker drone location projected in the top-down view of smoke using RANSAC
  - The smoke contour is detected, and mean line (skeleton) is calculated using the smoke contour
  - **Steady Smoke Flow (S)**: Constant streamwise wind (V_y) of 4.5 m/s with no fluctuations
  - **Unsteady Smoke Flow with Low-Frequency Horizontal Fluctuation (UL):** Mild low-frequency fluctuating crosswind - primary wind $V_y = 4.5$ m/s, crosswind specified $V_x = 1.35\sin(0.02\pi t)\ \mathrm{m/s}$ with an amplitude of 1.35 m/s and a frequency of 0.01 Hz.
  - **Unsteady Smoke Flow with High-Frequency Horizontal Fluctuation (UH):** Stronger high-frequency crosswind superimposed on top of the primary wind of $V_y = 4.5\ \mathrm{m/s}$, crosswind $V_x = 1.95\sin(0.04\pi t)\ \mathrm{m/s}$ with an amplitude of 1.95 m/s and 0.02 Hz frequency.
  - **Unsteady Smoke Flow with 3D Fluctuation (U3D):** Both horizontal and vertical wind fluctuations in the primary wind of $V_y = 4.5\ \mathrm{m/s}$. $V_x = 1.95\sin(0.04\pi t)$ (amplitude 1.95 m/s, frequency 0.02 Hz), and vertical wind $V_z = 0.3\sin(0.02\pi t)$ (amplitude 0.3 m/s, frequency 0.01 Hz).

Smoke Tracking Results

		$\tilde{\mu}_m$(%)	$\tilde{d}_{m,max}$(%)	$\tilde{\mu}_c$(%)	$\tilde{d}_{c,max}$(%)	$\tilde{t}_R$ (%)
S	PID	1.6±0.2	7.5±2.1	1.4±0.6	2.9±0.7	95.1±2.5
	DRL	1.4±0.2	7.0±2.3	1.8±1.2	4.0±3.3	94.1±1.4
UL	PID	4.0±0.4	11.9±2.2	2.5±1.3	6.6±3.1	87.1±2.2
	DRL	1.8±0.5	10.1±2.3	2.5±1.1	8.4±3.3	86.9±1.8
UH	PID	7.2±1.5	28.1±10.9	5.3±3.8	18.6±7.4	69.4±4.7
	DRL	5.4±1.1	26.0±8.4	4.6±3.1	12.3±6.5	85.0±6.4
U3D	PID	4.1±0.6	15.5±6.5	4.5±2.6	12.8±5.9	79.5±2.3
	DRL	1.9±0.5	10.6±4.4	1.5±2.1	4.3±4.3	95.0±4.1

- **Smoke tracking evaluation:**
  - The PID and the DRL controller performed almost the same in steady unidirectional flow and also in unsteady flow with low fluctuations according to the metric scores.
  - The DRL controller outperforms PID under challenging smoke conditions (U3D), staying inside the smoke almost 15% longer.
  - The DRL controller significantly reduces tracking error in unsteady environments, with a 12.3% maximum deviation compared to PID's 18.6% in high-frequency fluctuations (UH and U3D).
  - Under 3D fluctuation, DRL's avg. distance from the mean line to 1.9%, while for PID its 4.1%, showcasing the DRL's better adaptation to more realistic multidimensional smoke fluctuations.

Field Demonstration

Field Demonstration

Drone autonomously tracking smoke (top view)
[red bounding box shows the drone location within smoke]

Drone autonomously tracking smoke (side view)
[red bounding box shows the drone location within smoke]

- **Autonomous smoke tacking using drone simulation:**
  - Smoke Segmentation using yolov8-seg model
  - Autonomous drone movements using PID and DRL-based controller.
  - Deployment demonstrates the process of drone tracking the smoke along its flow path, and ultimately reaching the source of the smoke.

Future work and Conclusion

- Improve the Deep Reinforcement Learning based controller for smoother and more intelligent smoke tracking in more unpredictable smoke-wind scenarios.
- Deploy the tracking system in actual forest fire smoke.
- Have a master-worker drone swarm system in which the master drone will be outside the smoke to capture the smoke view from outside the smoke for more intelligent, accurate and robust tracking using the worker drones.

Questions