Exploring Autonomous Aircraft Taxiing in a Simulated Environment

Stanford AI4ALL Robotics Group

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Motivation Outline

- Advancements in autonomous Vertical Take Off and Landing (VTOL) and commercial aircraft.
- Autonomous aircraft contribute to climate change mitigation via optimized flight paths.
- Autonomy addresses economic concerns, such as the pilot shortage.
- Potential applications in autonomous delivery services (e.g., Zipline, Amazon).
- Integration of data-driven techniques (neural networks) with classical controls (PID).
- High safety standards through iterative testing and improvement in autonomy.
- Project focus on taxiing phase using X-Plane 11 simulator for controlled testing.

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(Zipline)


(Joby Aviation)

Motivation

- Autonomous aircraft development with several benefits.
- Contributes to climate change mitigation through optimized flight paths.
- Addresses economic issues, saving industries billions
- Potential in transforming delivery and logistics services.
- Enhances health and safety standards in aviation and critical medical deliveries.

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Motivation (cont.)

Autonomous taxiing reduces runway incursion risks, enhancing safety. It improves efficiency, minimizes delays, and boosts the passenger experience.

Operational Errors	Pilot Deviations	Vehicle/Pedestrian Deviations
Causes either less than the minimum required separation between two or more aircraft or between an aircraft and obstacles on runways, or results in an aircraft landing or departing on a closed runway	Violation of Federal Aviation Regulations by a pilot, such as disobeying air traffic control instructions like not crossing an active runway	Any pedestrians, vehicles or other objects interfering with aircraft operations by entering or moving on the runway movement area without authorization from air traffic control

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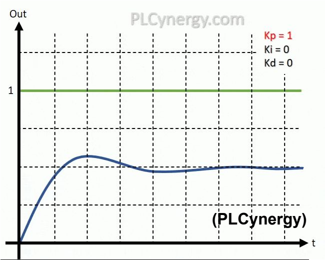
Motivation (cont.)

The integration of data-driven techniques and classical control methods forms the backbone of our autonomous aircraft system.

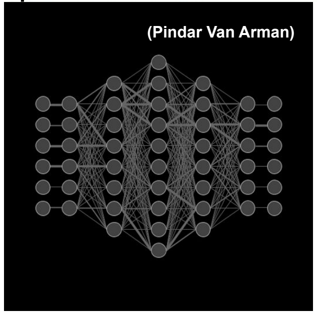
PID Control

By continuously adjusting the control inputs based on the error between the desired and the current state, PID control ensures accurate and smooth operation.



Neural Network

By learning patterns in the training data, it can anticipate and respond to a wide range of scenarios, thereby enhancing the AI's performance and decision-making capability in real-time operation.



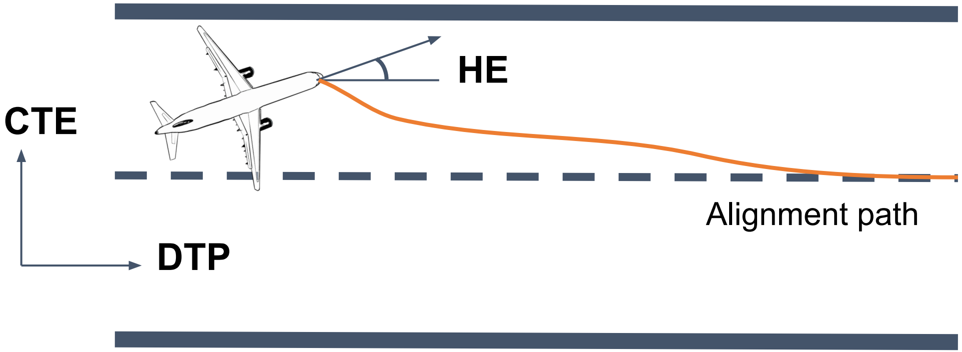
Methods Outline

- Problem Formulation
  - The objective is to position our aircraft such that it is collinear with the runway's centerline.
- Modules
  - Perception: camera on the nose of the plane
  - Estimation: neural network
  - Planning and Control: Closed Loop Controller (PID)
- Dataset
  - Input: 20,000 screenshot images from X-Plane
  - Output: crosstrack error and heading error to be used in controller

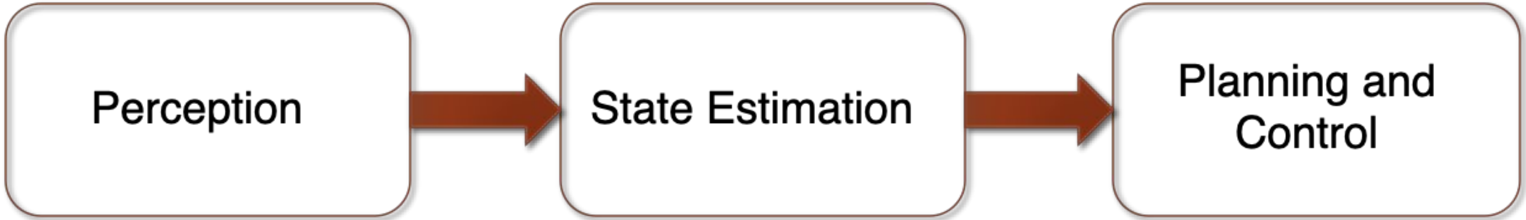
Problem Formulation

Goal: To maneuver our aircraft such that its heading direction is collinear with the runway's centerline.

Crosstrack Error (**CTE**): Lateral deviation from the centerline
Downtrack Position (**DTP**): Longitudinal deviation from the runway's starting position
Heading Error (**HE**): Angular difference between the aircraft's direction of travel and the centerline



Autonomy Stack



- **Perception:** Generates observations of the agent’s environment.
- **State Estimation**: Generates an estimate of the agent’s state, given its observations.
- **Planning and Control**: Decides the goal of the agent and the control inputs to get the agent to its goal.

Autonomy Stack Outline

Perception: Individual screenshots serve as the primary perceptual data for the system, offering essential visual information that can determine the aircraft's position relative to the runway.

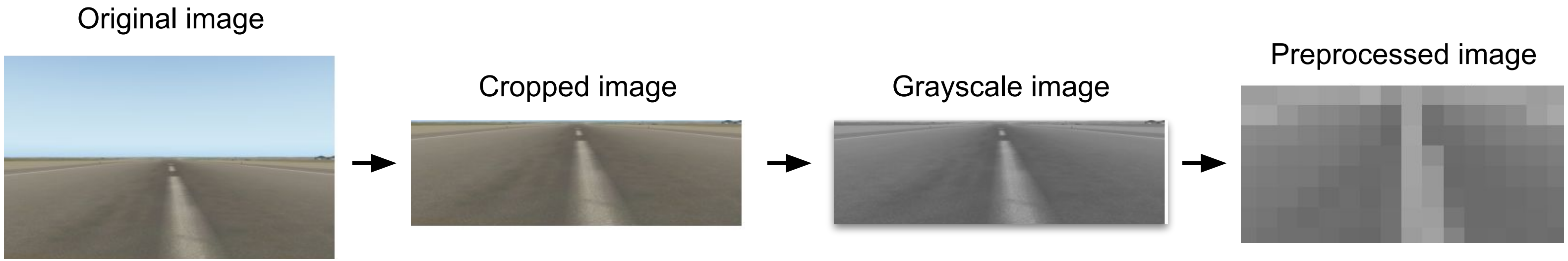
Estimation: A neural network digests the static images provided by the perception system and employs trained models to deduce the aircraft's alignment with the runway's centerline.

Planning and Control: The PID controller aims to minimize the error between the estimated and desired states, thereby ensuring that the aircraft is correctly aligned with the runway's centerline.

Perception

Sensor: Utilizes a camera sensor mounted on the aircraft's nose. The camera captures images, serving as input for the neural network.

Data Preprocessing: Cropping, converting to grayscale, and applying an averaging filter, effectively downsampling the image for processing by the neural network.

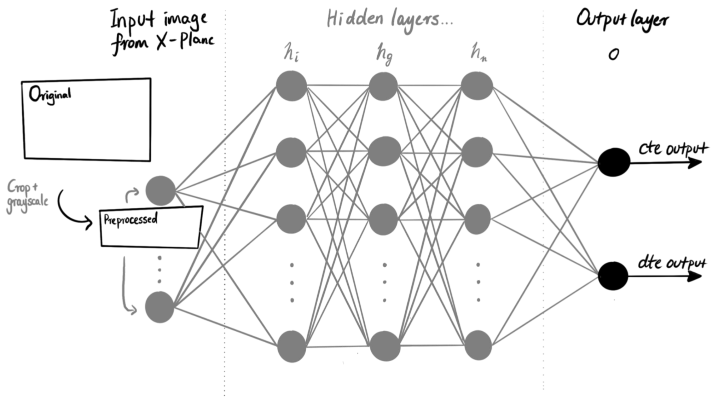


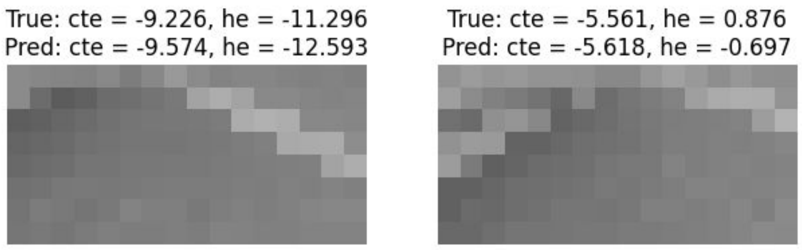
State Estimation

Neural network: 5-layer fully-connected network

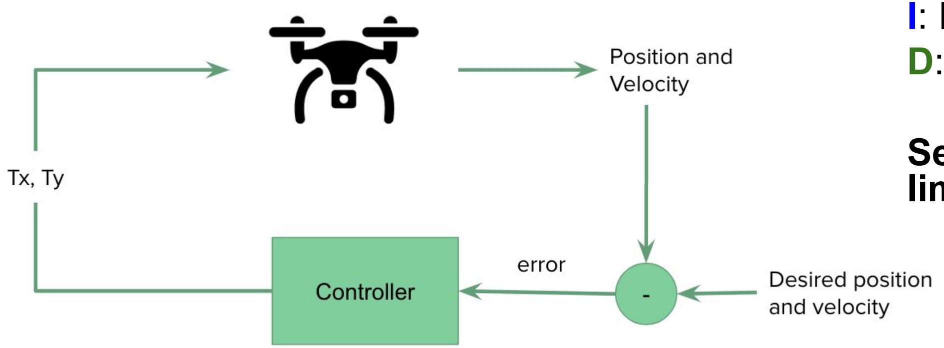
- The layers consist of 128, 256, 64, 32, and 2 nodes respectively.
- A learning rate of 0.0001 is applied.
- Rectified Linear Units (ReLU) are used for activations.
- The mean squared-error loss function guides learning.

Dataset: 18,000 training images/labels and 2,000 test samples





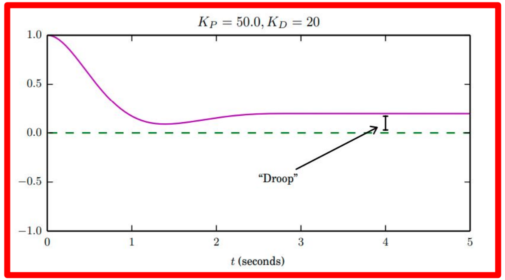
PID Controller

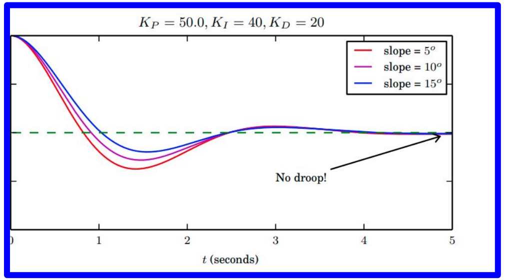


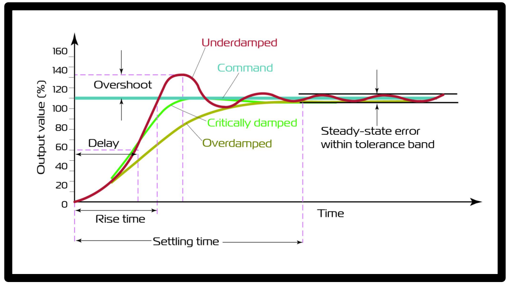
P: Proportional - current error
I: Integral - *sum* of error over time
D: Derivative - rate of change of error

Select PID gains for fast response with limited overshoot.

$$\tau = \boxed{k_p e} + \boxed{k_v \dot{e}} + \boxed{k_i \int e}$$

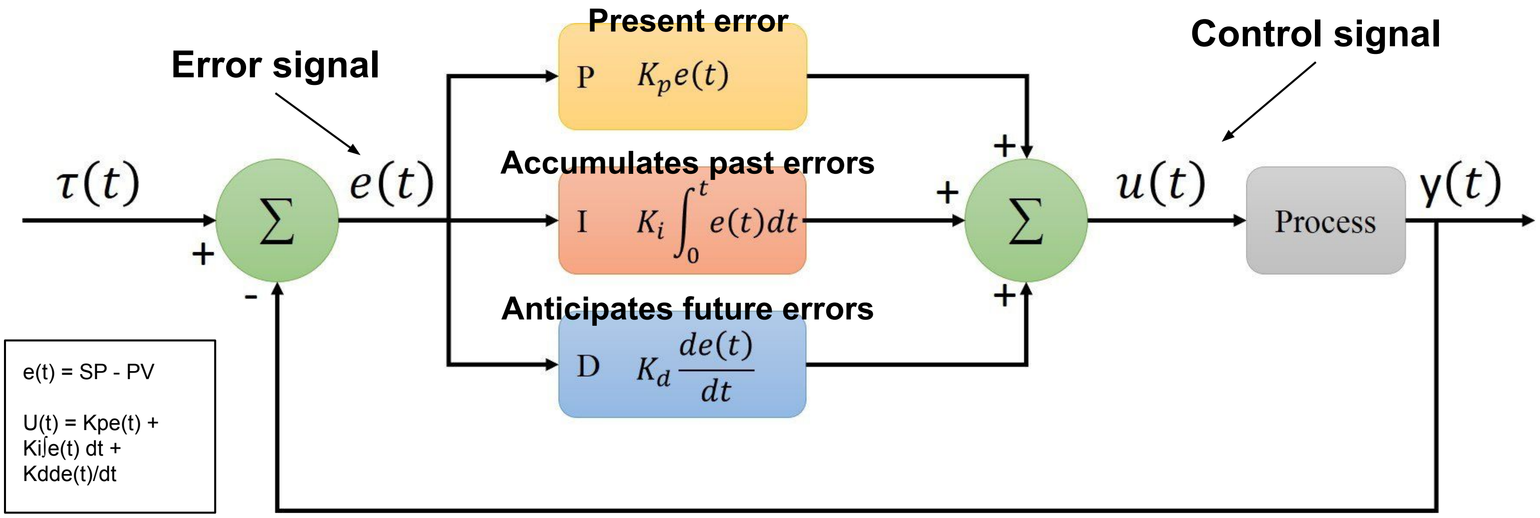






Explanation: PID controller

A PID controller operates based on a closed-loop feedback control system, continuously monitoring the difference between the desired setpoint (SP) and the actual process variable (PV).



e(t) = SP - PV

U(t) = Kpe(t) + Ki∫e(t) dt + Kdde(t)/dt

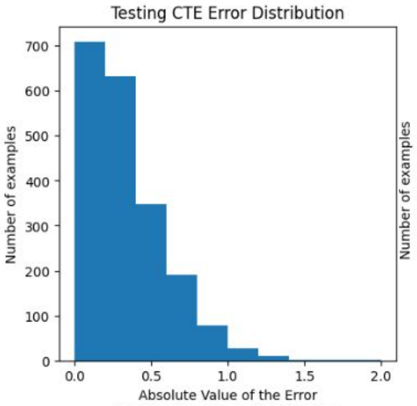
Initial Training Data

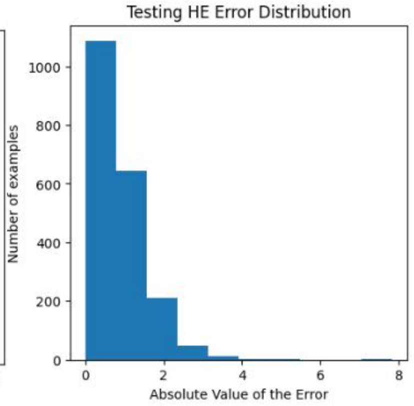
What do these histograms mean?

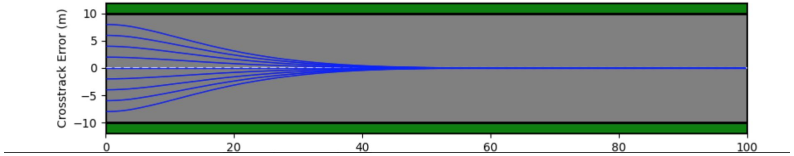
These histograms show the error distributions during testing. The CTE had a maximum offset of 1.5 meters, while the HE had a maximum error of 4 degrees.

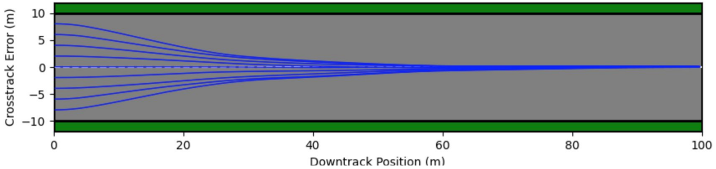
What are the graphs showing?

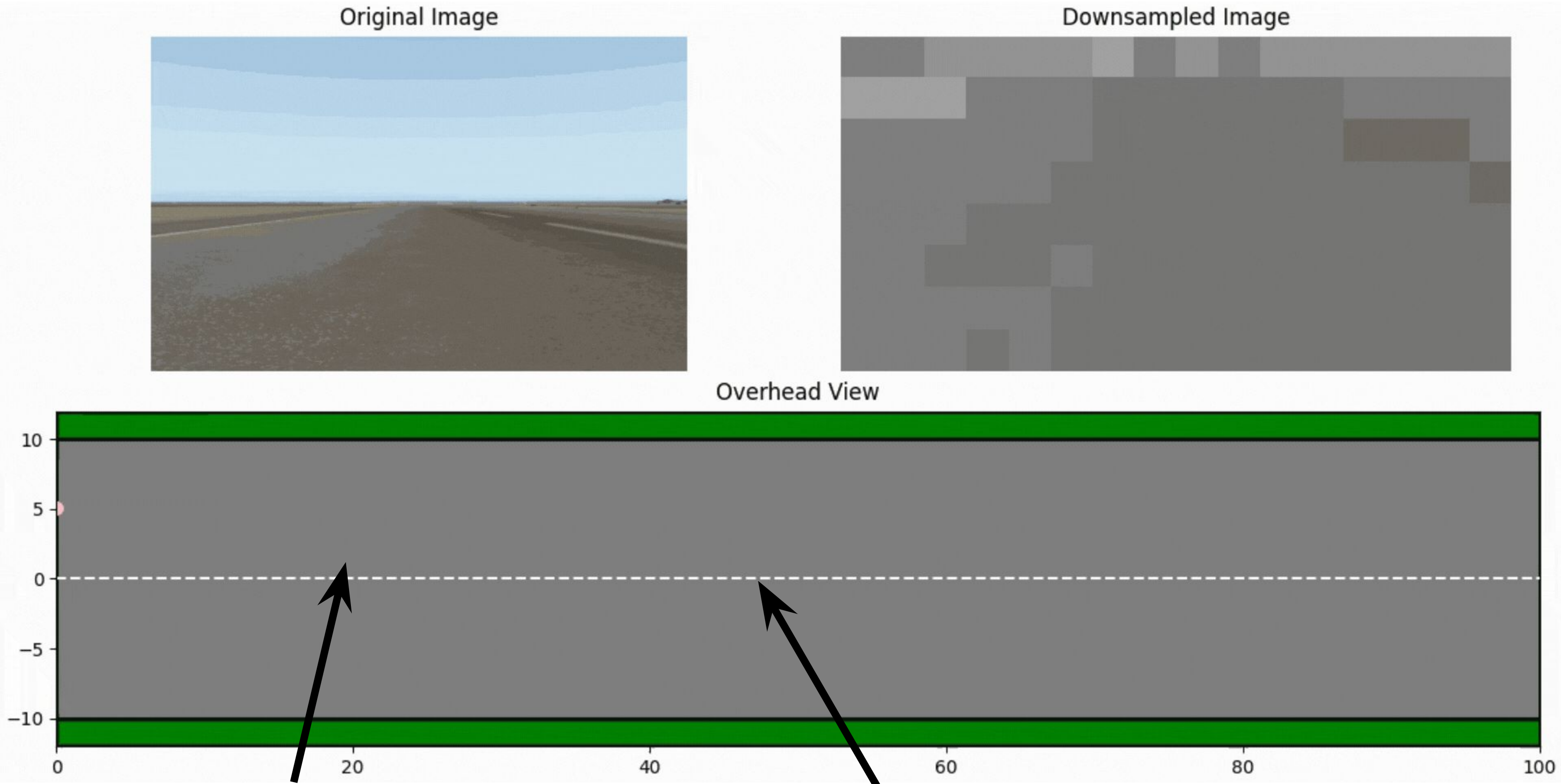
The top graph assumes that we have perfect knowledge of our location, while the second one is a more realistic model using sensors.











Pink dots - expected trajectory values from the neural network

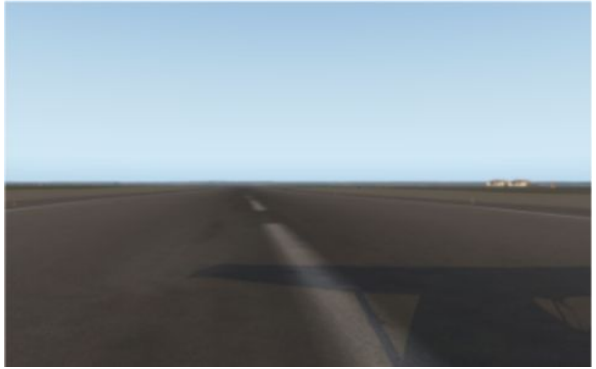
Blue line - Actual trajectory followed by the aircraft

Environmental Conditions

What if we change the time of day and weather condition settings for the simulator?

- Simulator settings were adjusted to test the system under various environmental conditions.
- *Time of day* setting was changed to 5 pm to evaluate the impact of the aircraft's shadow.
- *Weather* setting was adjusted to an overcast sky scenario to assess performance under reduced visibility.
- These tests aim to ensure the system's robustness, safety, and reliability.

X-Plane (simulator) settings



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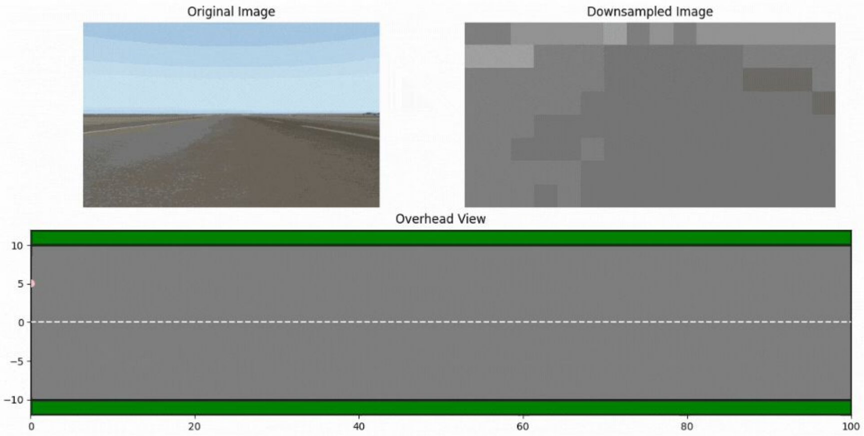
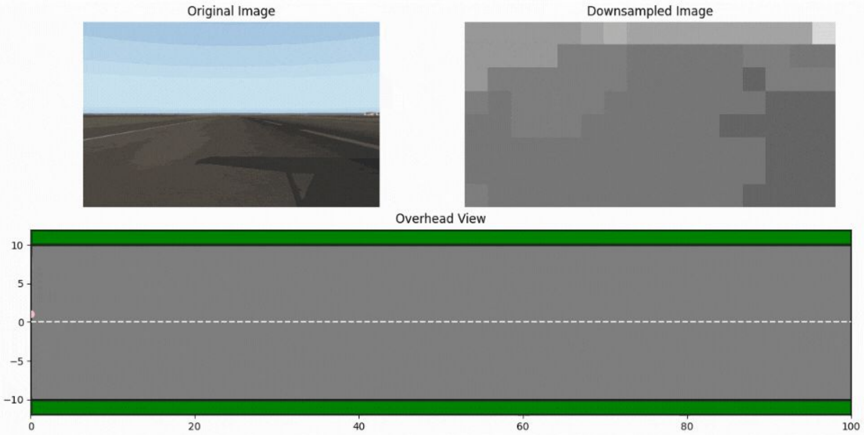
Results

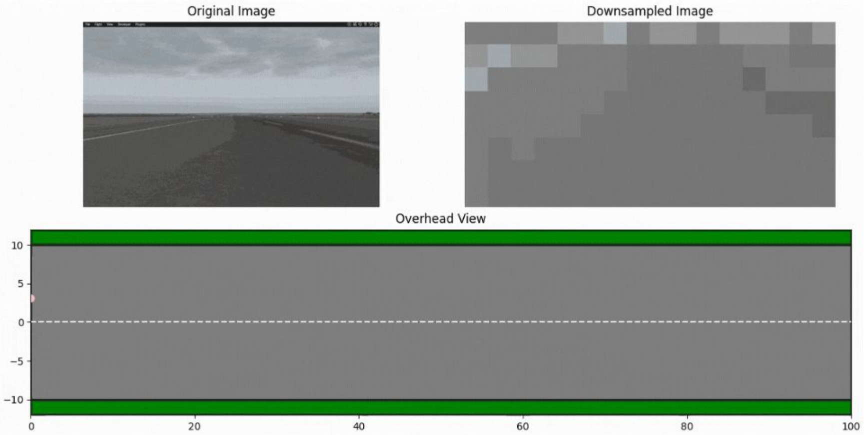
Top right: Clear sky

Bottom left: With the plane shadow

Bottom right: Cloudy sky







Conclusion

- Motivation
  - Climate and economic benefits
  - Efficient product delivery
  - Potential job losses due to automation
- Methods
  - Camera for perception
  - Neural network for estimation
  - PID control for planning and control
- Results
  - Good performance in clear and cloudy conditions
  - Inconsistencies when dealing with shadows
- Next Steps
  - Plan to train the system on more diverse data
  - Use search algorithms on graphs for better flight planning