Can image and sensor data be collected from remote airborne devices, for ground-based processing?

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Overview Our project integrates engineering and data science to explore if aerial image and sensor data can be collected and transmitted from airborne devices at long range, for real-time ground-based AI processing (processing that occurs online back on the ground as the data is received). The goal was to construct a pre-programmed payload containing a Raspberry Pi (minicomputer) and its peripherals (air quality sensors and camera) to survive automated data collection during airborne deployment on a high-altitude balloon and research rocket, for local environment aerial data collection.

Aims To investigate if locally collected data may be retrieved at long-range from airborne Raspberry Pi devices for live, cloud-based AI processing. Machine learning processing will implement image recognition and predictive linear regression algorithms to discover environmental features in images (Fig. 2), and correlate local air quality sensor data (Fig 1) with similar historical Earth observation data (Fig 3).

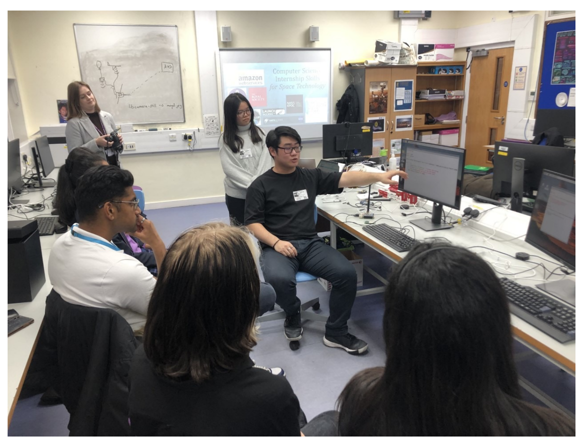
Background information Physical computing uses interactive sensors that respond to a computer's immediate environment. In our experiment, we used Raspberry Pi computer peripherals to collect air quality sensor and camera image data for transmission to another ground-based 'receiver' Pi computer, via long-range LoRa radio. Image data was collected for computer vision feature recognition processing, and numerical sensor reading data (humidity and nitrogen dioxide–NO_2) collected for correlation with historical Earth satellite data from the same location. Once plotted and correlated, regression lines were then created to model predictions about the relationships between the air quality data sets. All processing was programmed to take place on the cloud (online).

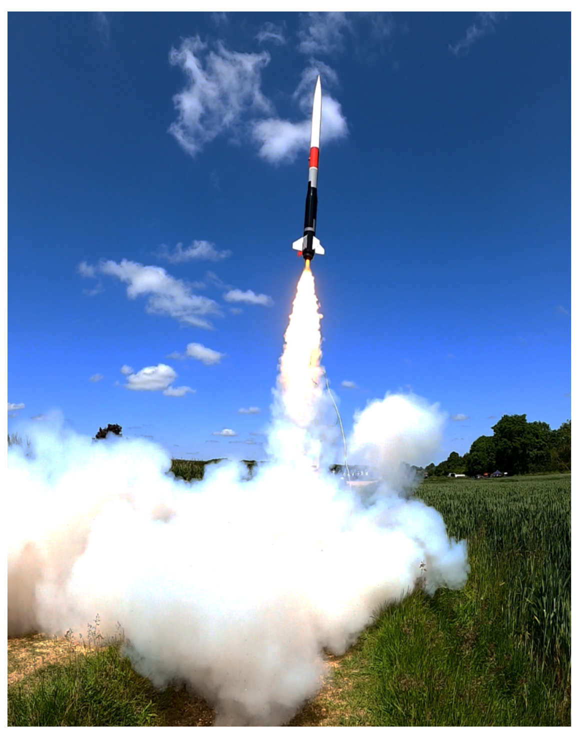
Methodology

1. We programmed Raspberry Pi devices to capture and save sensor and image data.
2. We programmed a transmitter to send the saved data. We trialled this in the classroom to test the speed and efficiency of transmission.
3. We optimised the survival placement and powering requirements of the Raspberry Pi devices as retrievable payloads for high altitude balloons (HAB) and model rockets.
4. We prepared machine learning models for image recognition and predictive analysis, responding to our locally collected data, image archive data and historical satellite data.
5. We programmed cloud-based AI applications to process uploaded image and numerical sensor data, transferred from Raspberry Pi's.

L	M	N	O
pressure	no2_we	no2_ae	humidity
102664	0.23848	0.23687	3.3
102659	0.23848	0.24009	3.5
102670	0.24089	0.23848	3.4
102681	0.2417	0.23687	3.2
102658	0.23525	0.23848	3.5

Fig.1 HAB sensor data





Results Whilst the LoRa radio transmitter failed to send sufficient image data through due to file weight, the atmospheric sensor data was able to be retrieved, cleaned and plotted successfully. Our 2023 sensor data was seen as outlier when compared to the historical satellite data. Our payload's camera and air quality sensors were of a different standard to those collecting similar data by satellite, as they were prepared for HAB and rocket payloads, to survive and collect at substantially lower altitudes than satellites.

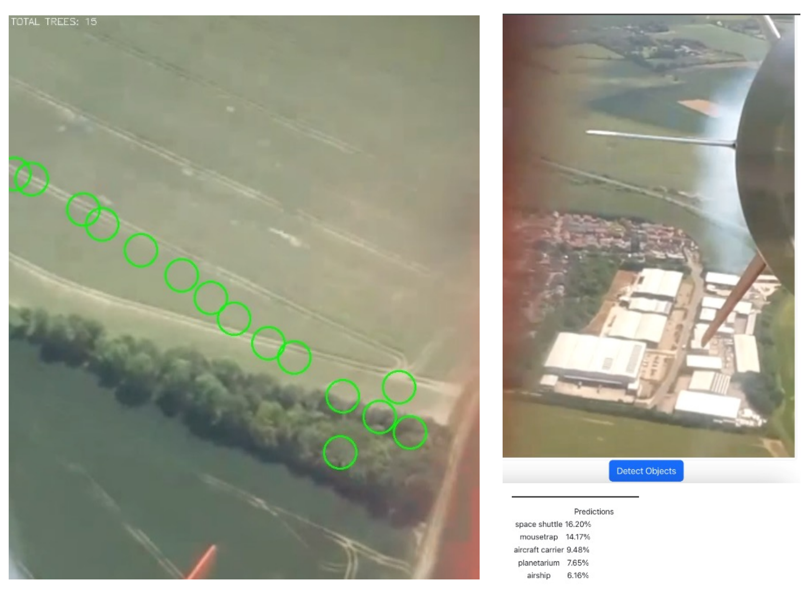


Fig.2

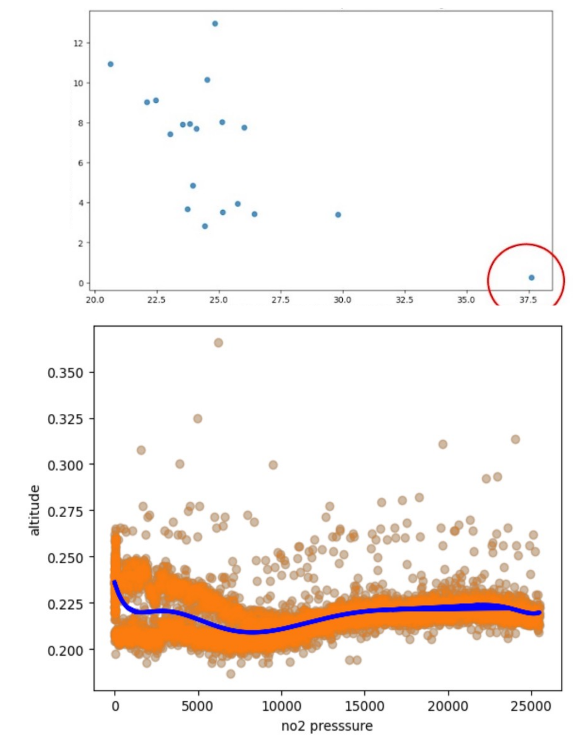


Fig.3

Conclusion

We considered possibilities to manipulate local or satellite data to make the two datasets more alike, via the mathematical process of normalisation. Looking at images collected from our airborne Raspberry Pi camera, its low-resolution images may similarly not match up in resolution or scale differently to satellite imagery. Exploring other research in the area, we anticipate an adapted 'regridding procedure' may be feasible on satellite air quality data, as it has worked for improved performance when correlating NO_2 data collected from the Earth's surface[1][2]. Similarly, a 'super-resolution' process might be anticipated to artificially enhance low-resolution images for improved image recognition AI, as investigated in other recent studies[3][4].

Evaluation and next steps

Discovering our image data could not be transmitted efficiently enough for real-time processing using LoRa radio, we anticipate a trial solution may be to run a pre-trained image recognition model directly on a Raspberry Pi computer itself. Images would be collected for feature recognition processing during flight, and more manageable 'abstracted' version aerial image data (adapted text-based information for symbolic image reconstruction) transmitted by LoRa radio for processing and visualisation via the ground-based cloud application.

References: 1. Cersosimo et al. (2020). TROPOMI NO2 Tropospheric Column Data: Regridding to 1 km Grid-Resolution and Assessment of their Consistency with In Situ Surface Observations, 12(14), 2212. 2. Geffen et al (2019). S5P TROPOMI NO 2 slant column retrieval: method, stability, uncertainties and comparisons with OMI, 13, 1315–1335 3. Affine. (2022). Super-Resolution With Deep Learning For Image Enhancement, Medium. 4. Zhu, F. (2022). A Review of Deep Learning Based Image Super-resolution Techniques, Xihua University.

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