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Machine Learning-Based UAV Localization for Under-Structure Sensor Deployment in GPS-Denied Environments

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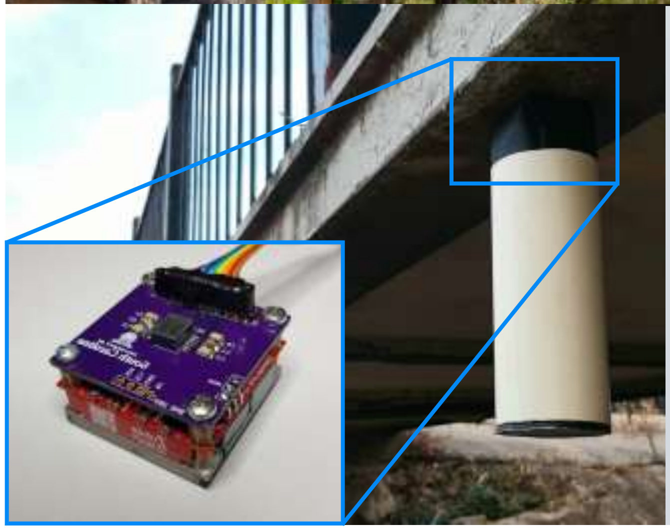
Outline

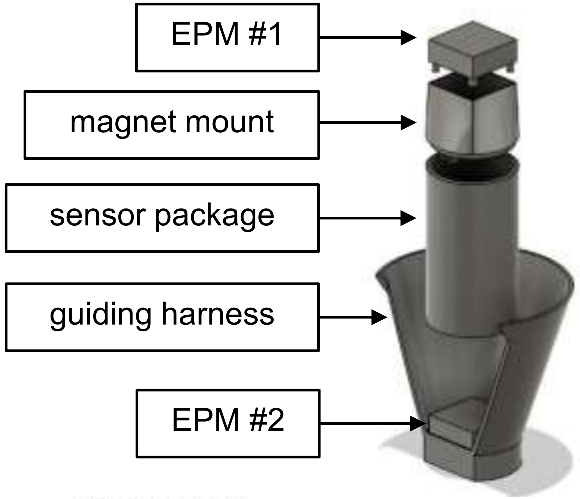


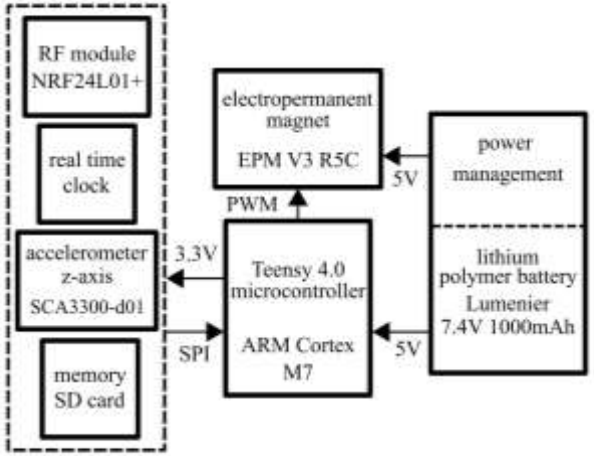
1. Background
2. UAV system and test site
3. Methodology
    1. YOLO based UAV recognition
    2. ML based localization
4. Results
5. Conclusions

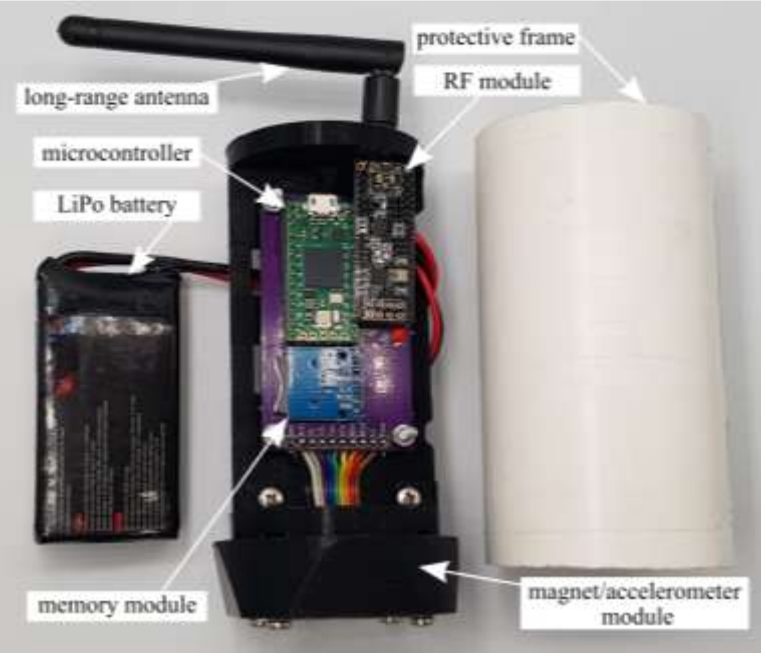
Background

UAV structural health monitoring

- Unmanned aerial vehicles (UAVs) have had an increasingly important role in the structural health monitoring (SHM) of aging infrastructure.
    - Requires less personnel
    - Safer
    - Cheaper
    - Faster
- Various UAV-based solutions have shown considerable results in the SHM environment.
- Physical sensor placement by UAVs show promising results in long-term monitoring.



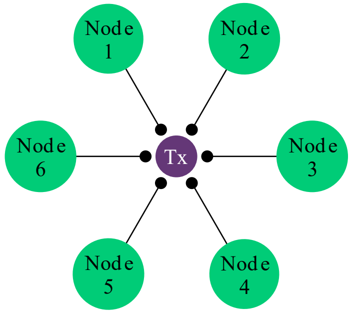


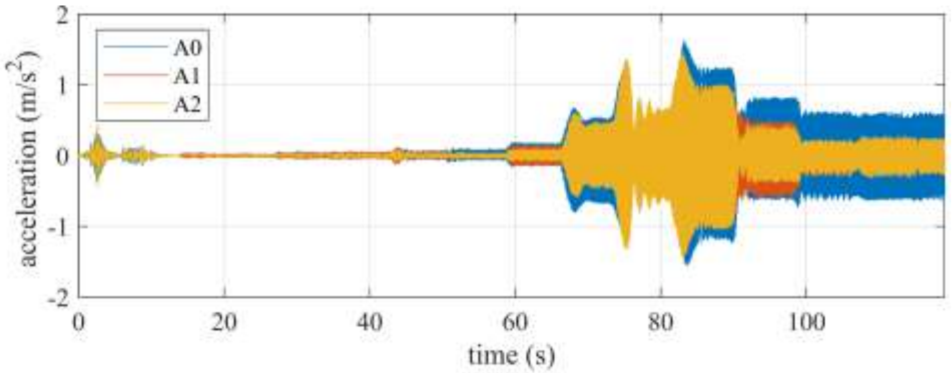


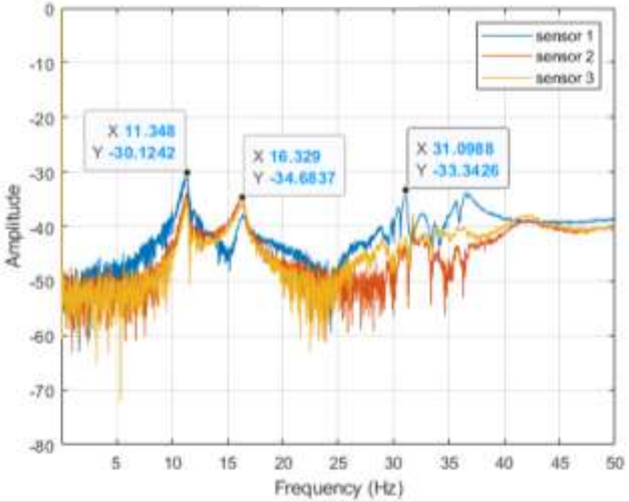
Background

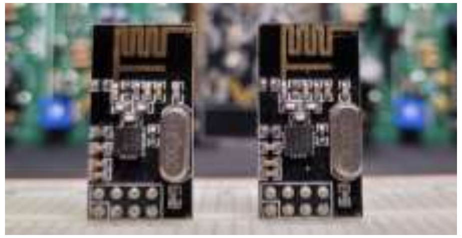
Wireless sensing networks

- Wireless sensor packages with electro-permanent magnets (EPMs) are delivered by UAVs, which “dock” sensors onto metallic structures by activating/deactivating the EPM during flight.
- Sensors measure vibration data to study the natur[e] frequency of civil structures.
    - 2.4 GHz ISM Bandwidth
    - Enhanced ShockBurst protocol
    - Wireless range of 100 meters
    - Transmission rate of 2 Mbps
    - Up to six radio links per hub
    - Ultra-low power consumption



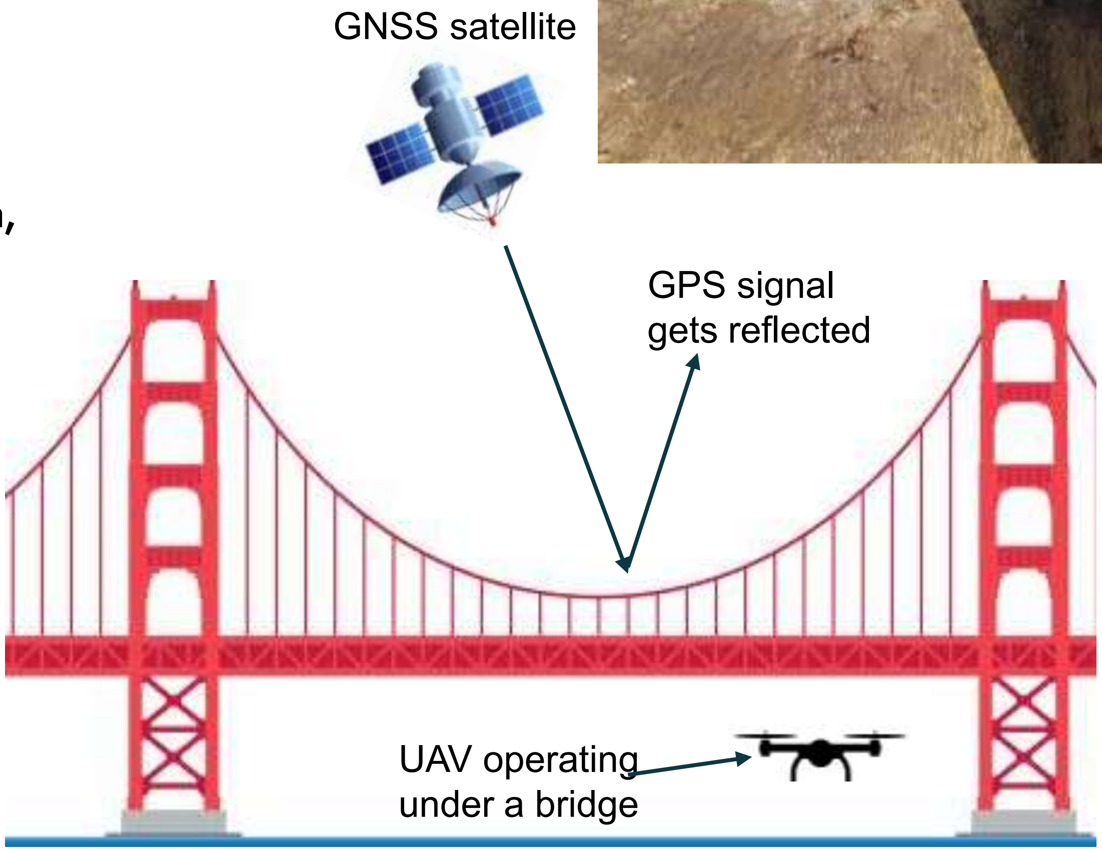






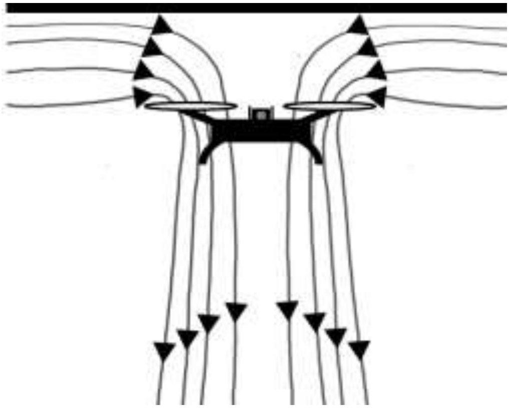
Line-of-sight and GPS signal

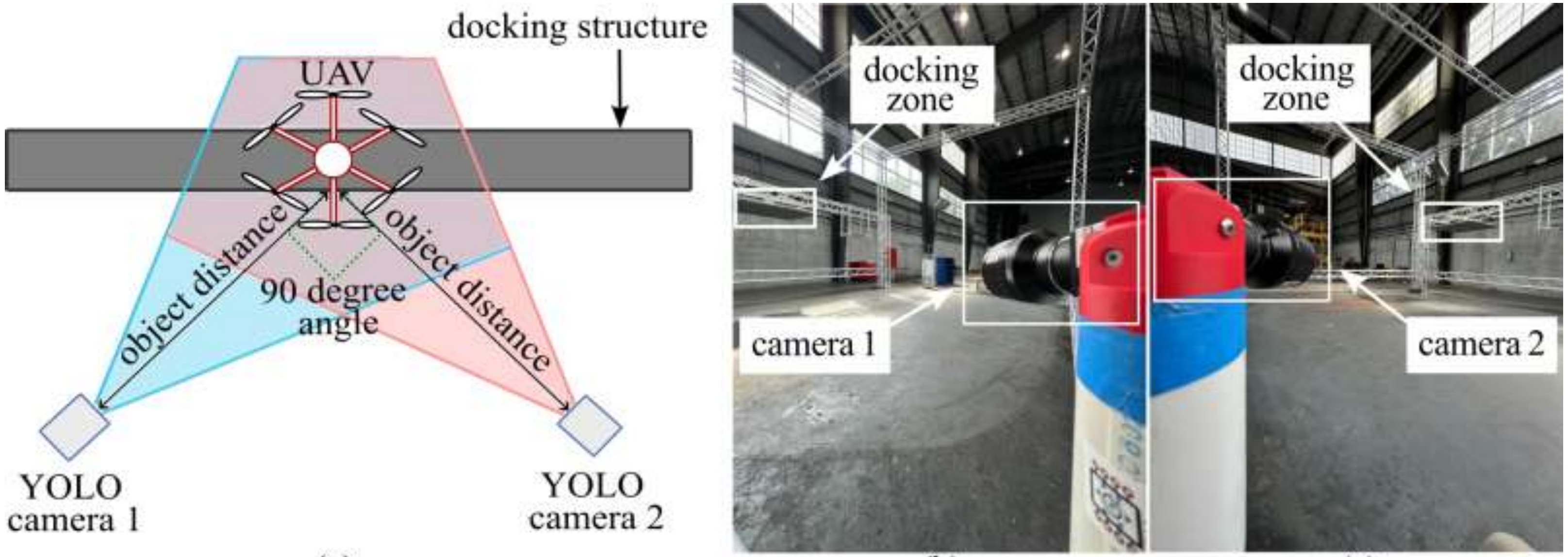
- UAVs are often manually piloted under structures to place sensors for analysis.
- Placement via manual control often leads to imprecise navigation during deployment.
- Line-of-sight issues complicate UAV navigation, as explained in the video on right.
- GPS signals near large metal structures (or indoors) suffer from signal blockage and multipath reception, affecting accuracy.
- As a result, UAVs struggle to stabilize in 3D space for sensor placement under metal structures.



UAV ceiling effect and external vision

- Ceiling effects can further complicate manual control. UAV thrust significantly increases, as the distance from the propeller to the ceiling decreases.
- Trained object-tracking algorithms on the UAV on stereo cameras allow for three-dimensional detection and tracking.
- This approach allows for tracking of the sensor docking process without the need for structural modifications.

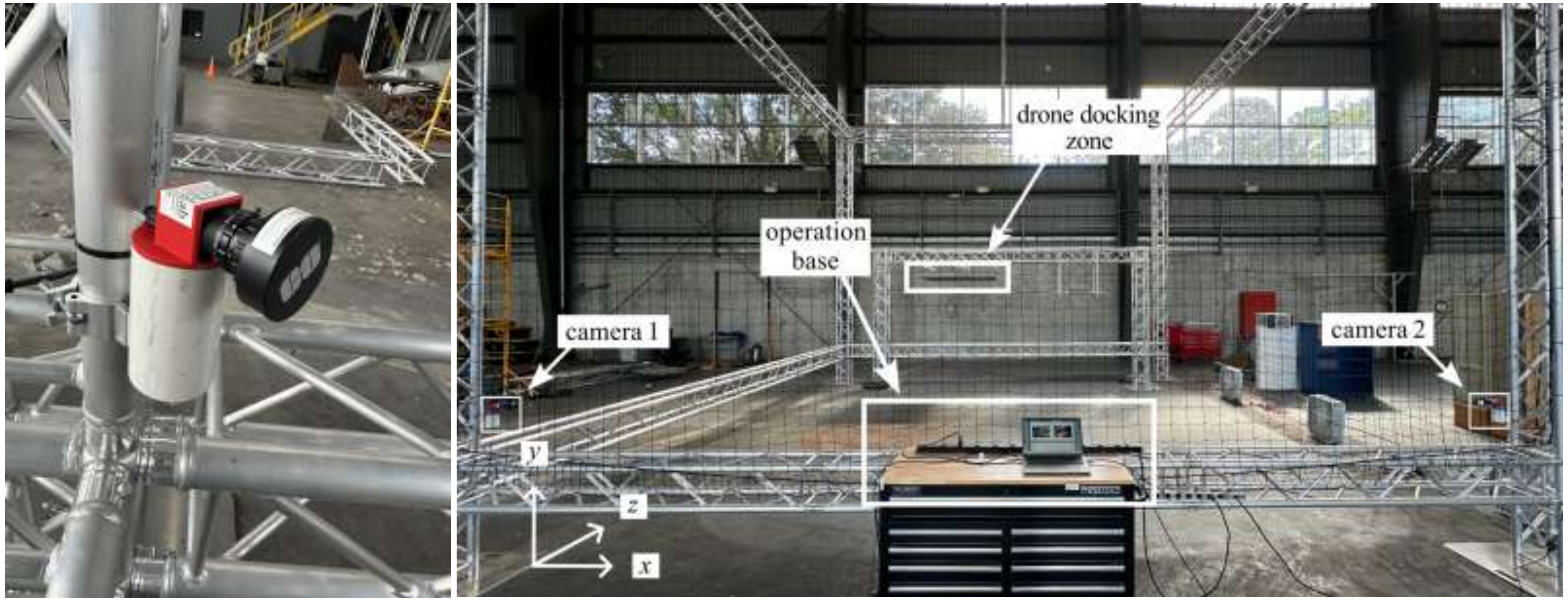




(a) (b) (c)

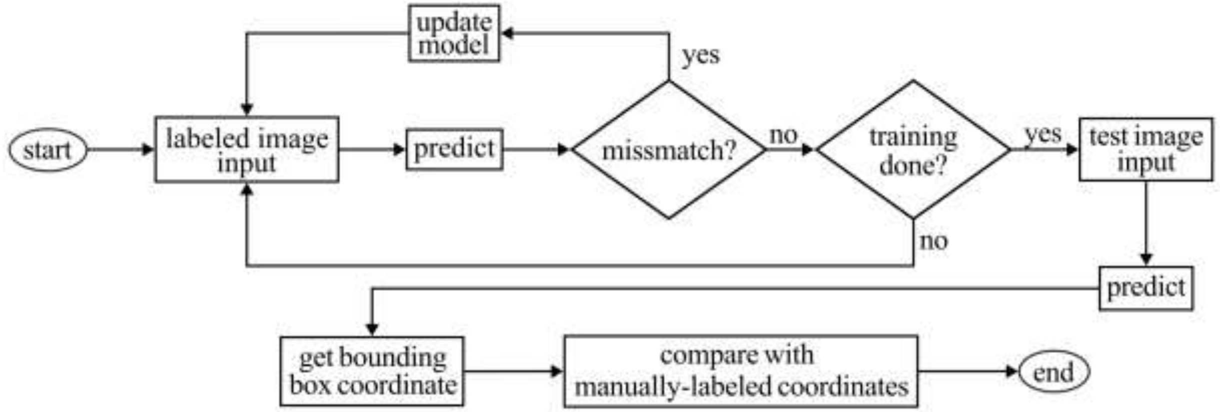
UAV system test site and technical aspects

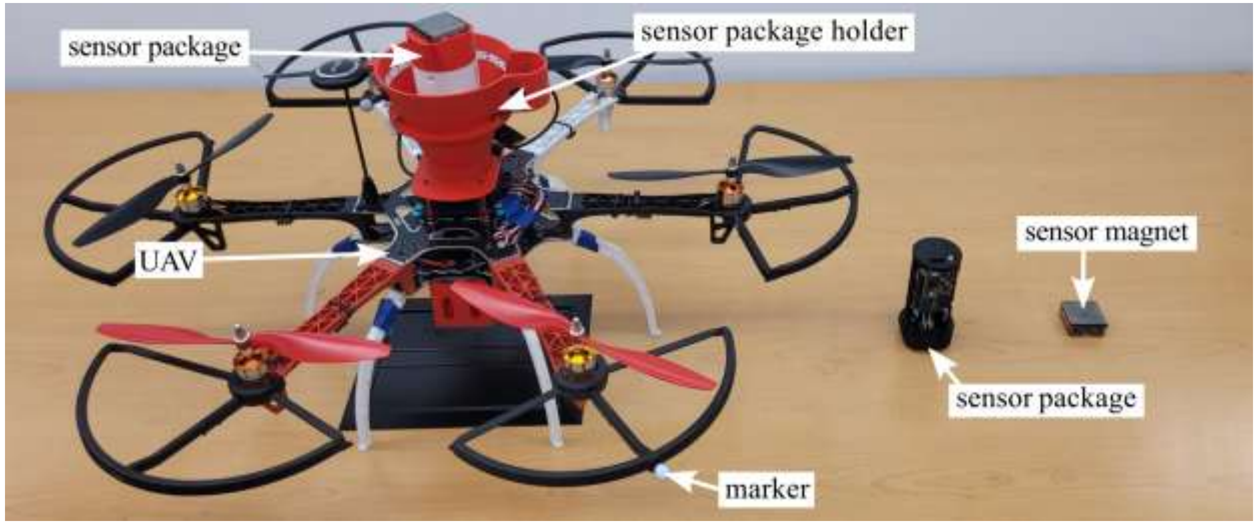
- Utilizes a metallic structure, UAV, and sensor package. Metallic structure consists of three large beams with a horizontal “docking zone”.
- The UAV is equipped with an electro-permanent magnet-based sensor deployment mechanism.
- Two 2.8 mm focal length color-cameras were positioned at a 45° angle to the left/right of the central axis facing the structural docking zone (ferrous metal plate 152.3 x 152.3 cm in length/width)
- Cameras were positioned on support beam intersections, with the right and left cameras 7.065 m and 5.980 m from the center of the docking zone, respectively. Cameras were mounted 1.055 m from ground level.



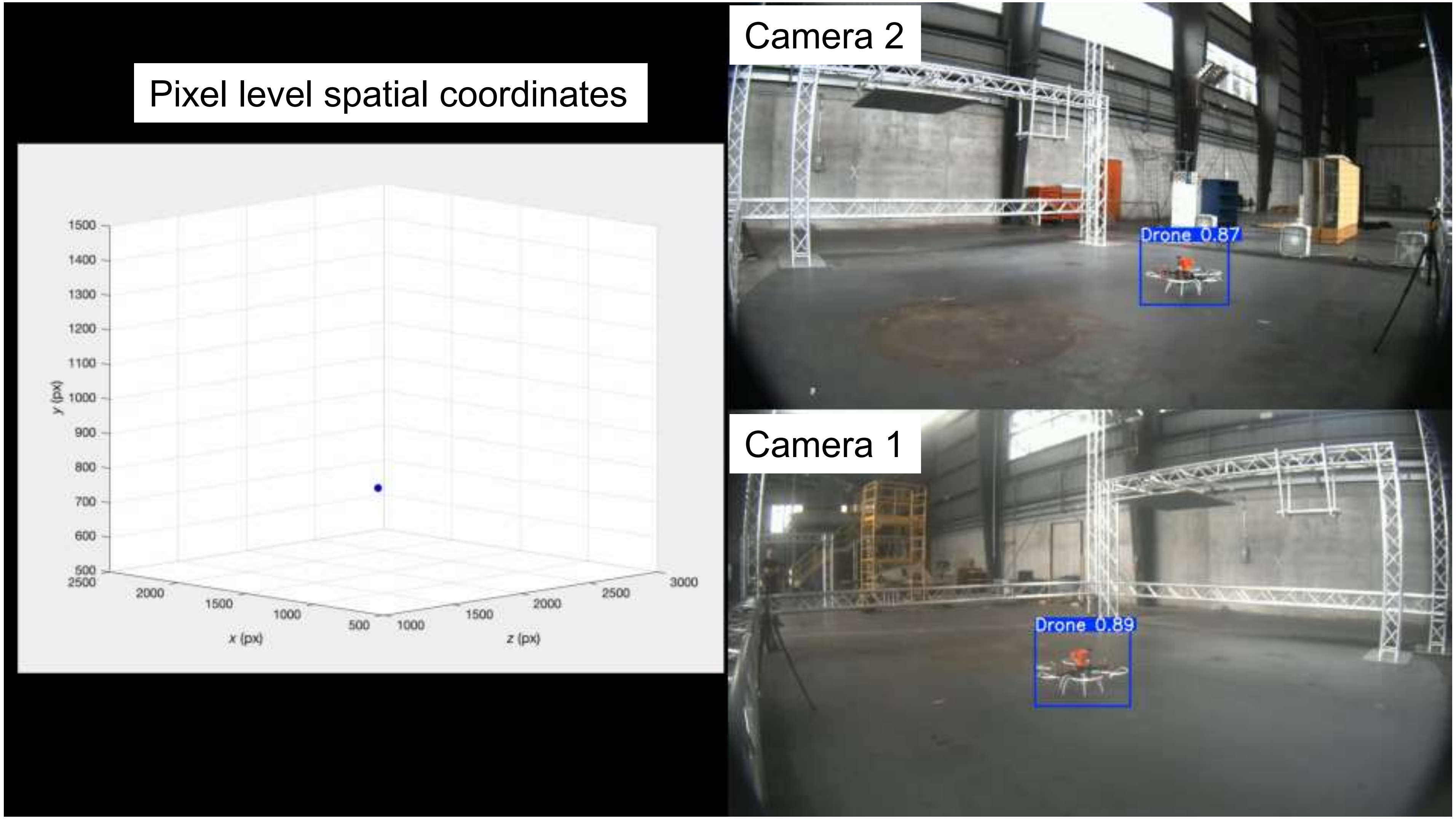
UAV recognition with You Only Look Once (YOLO)

- 64 hand-labeled images of the UAV in the test environment were used for training, including a 6-image validation group after each training session.
- Confidence-threshold, intersection over union, and frame rate were adjusted for improved detection
- 55-second test flight was used for evaluation between YOLO system UAV coordinates and manually-labeled coordinates
- Linear interpolation was applied between video frames, and differences between coordinates were interpreted as YOLO "error"



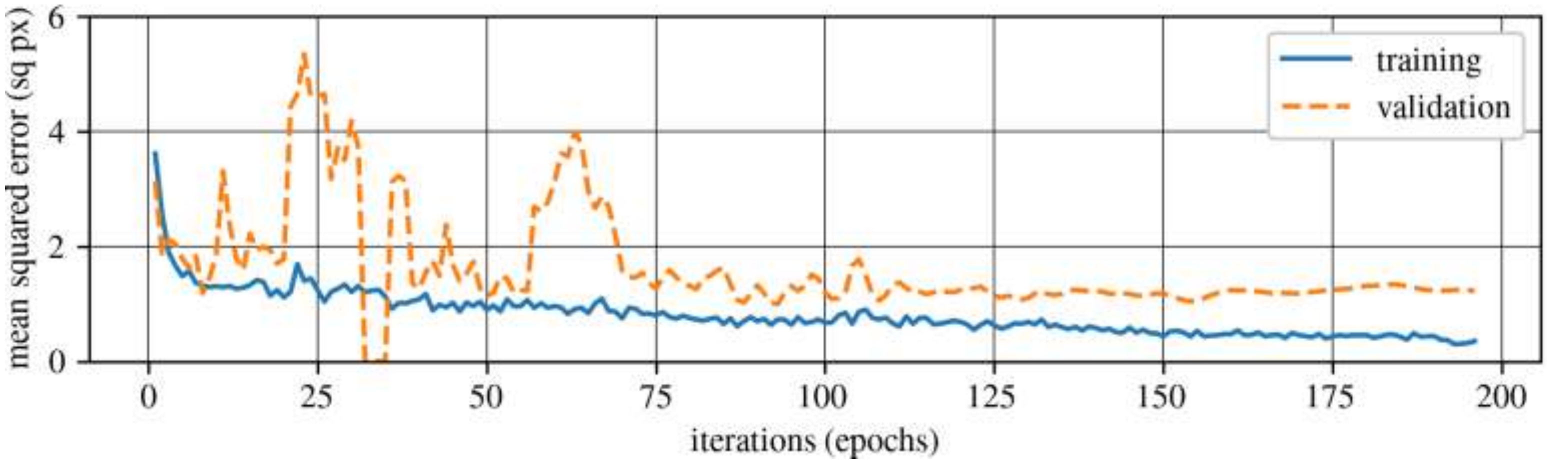


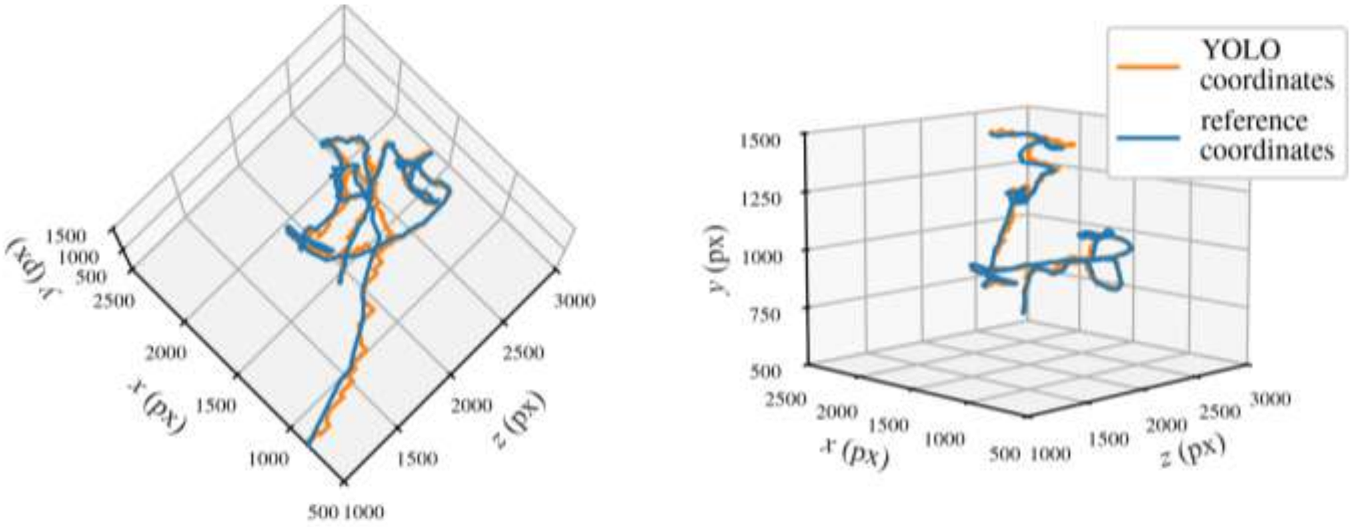
UAV recognition with You Only Look Once (YOLO)



UAV recognition with You Only Look Once (YOLO)

- Final YOLO model had a training box loss of 0.770 sq px and a validation box loss of 1.227 sq px by 96 epochs
- Validation errors showed more stability with more epochs, while training errors showed continual improvements
- **Machine-learning-based tracking systems can be readily developed to provide accurate positional data of UAV sensor docking**

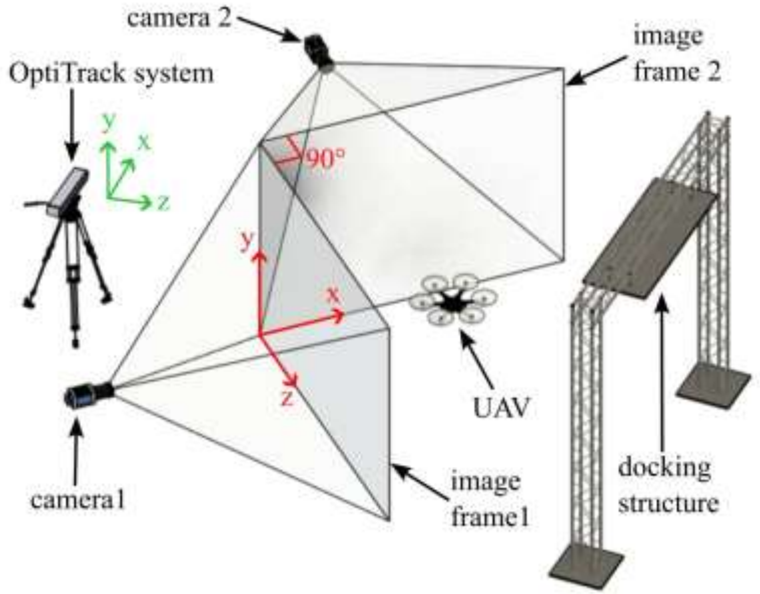


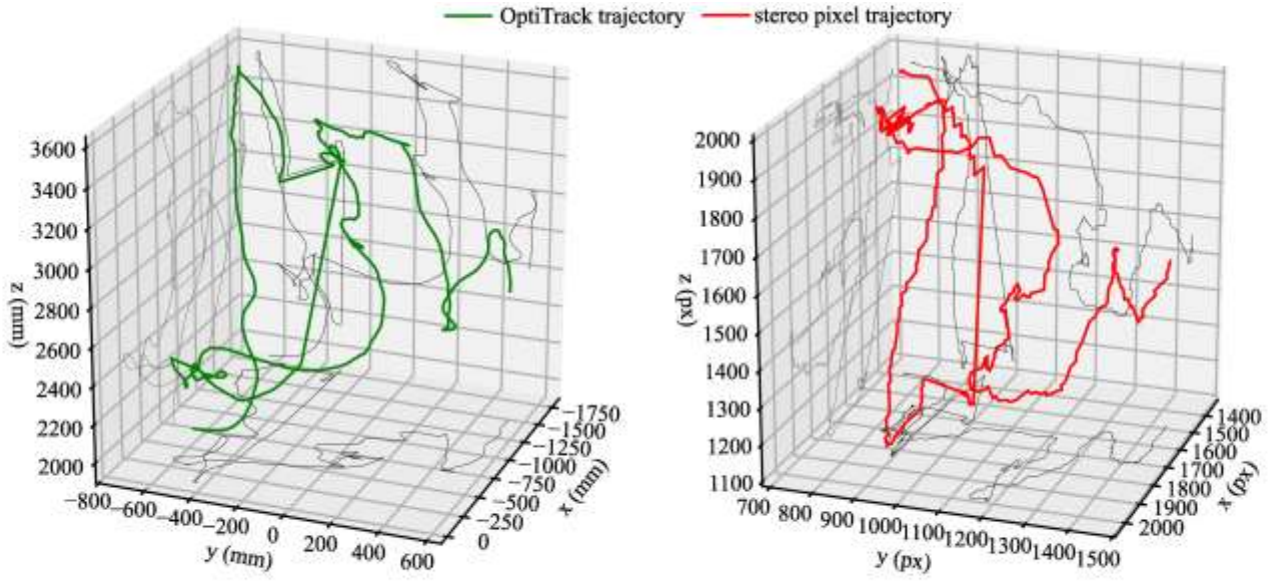


(a) (b)

Creating 3-dimensional spatial coordinates with ground truth

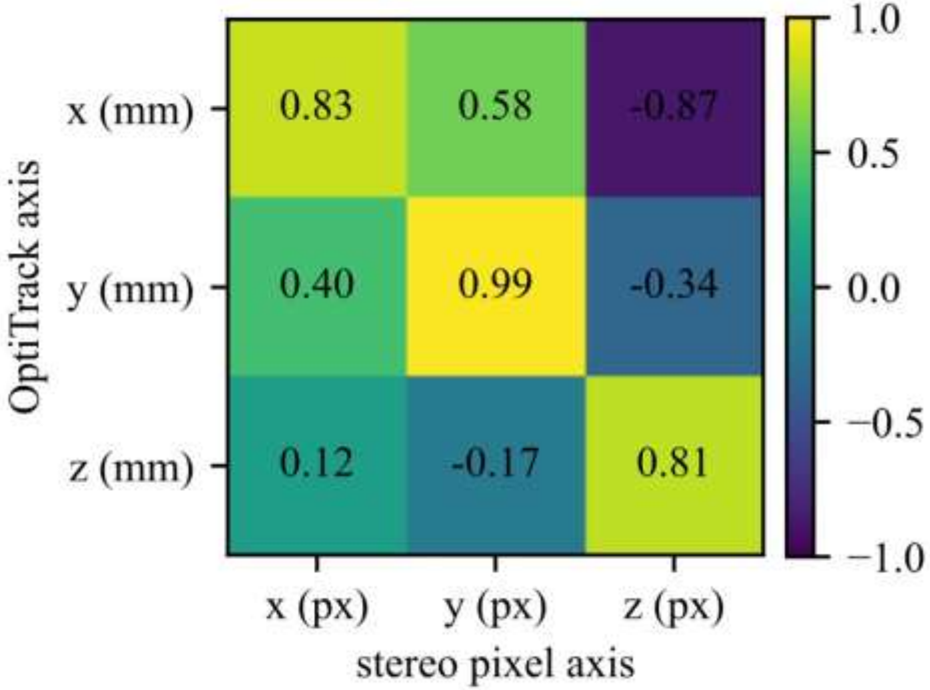
- YOLO based recognition is applied on both camera frame to get the stereo pixel coordinate of the UAV.
- An optical tracking system, OptiTrack, uses IR filters to track IR markers on the UAV, working as a ground truth for mm-level spatial coordinate ML training.

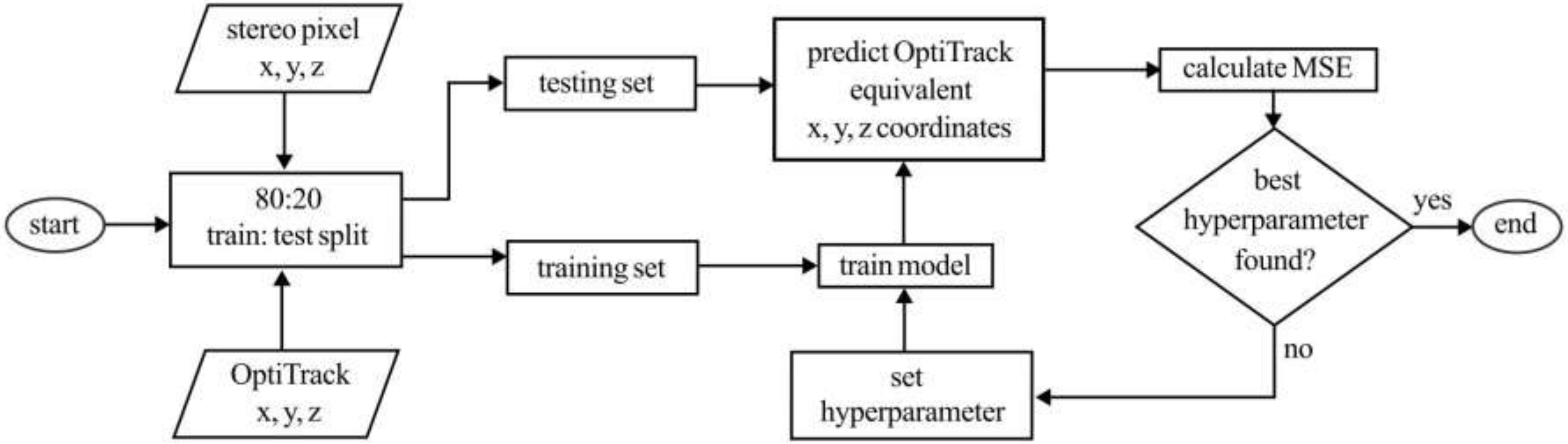




Tracking system linearity

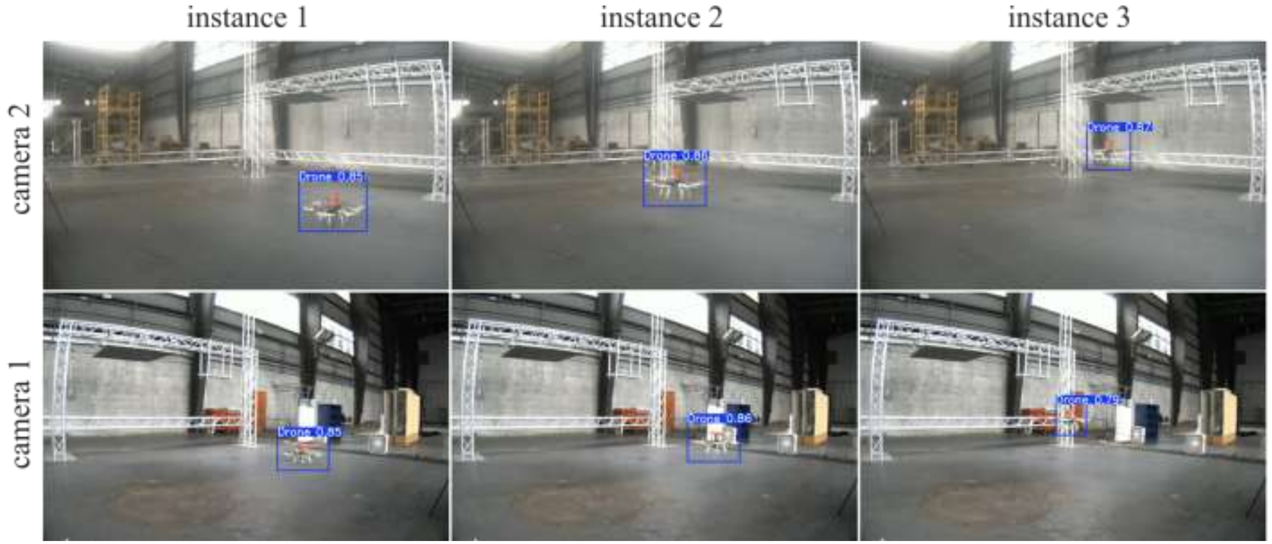
- The Pearson correlation matrix shows that pixel-based YOLO coordinates are not linear with their spatial distance coordinates.

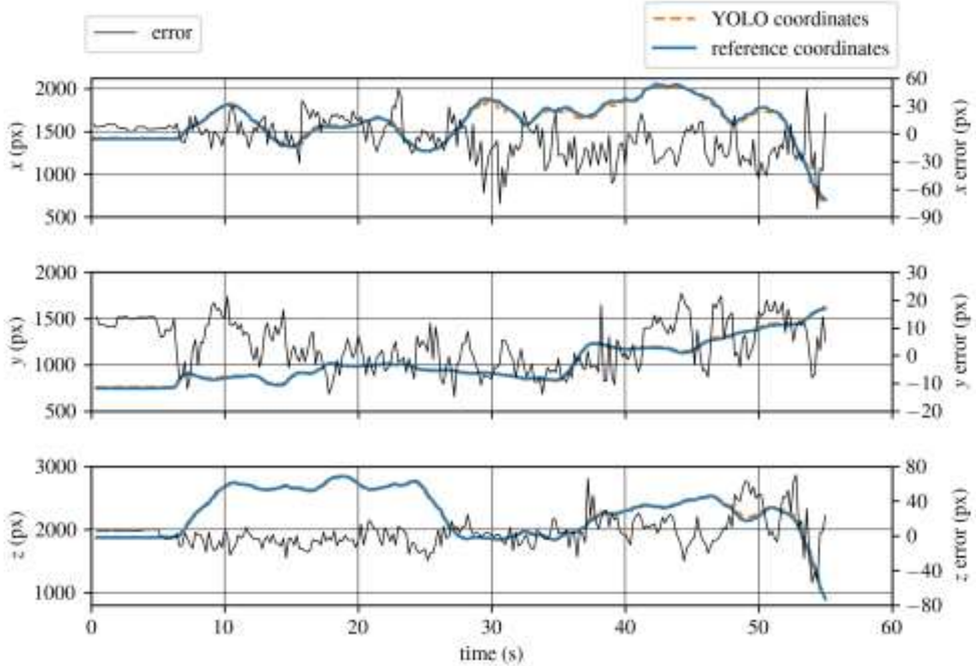




Results

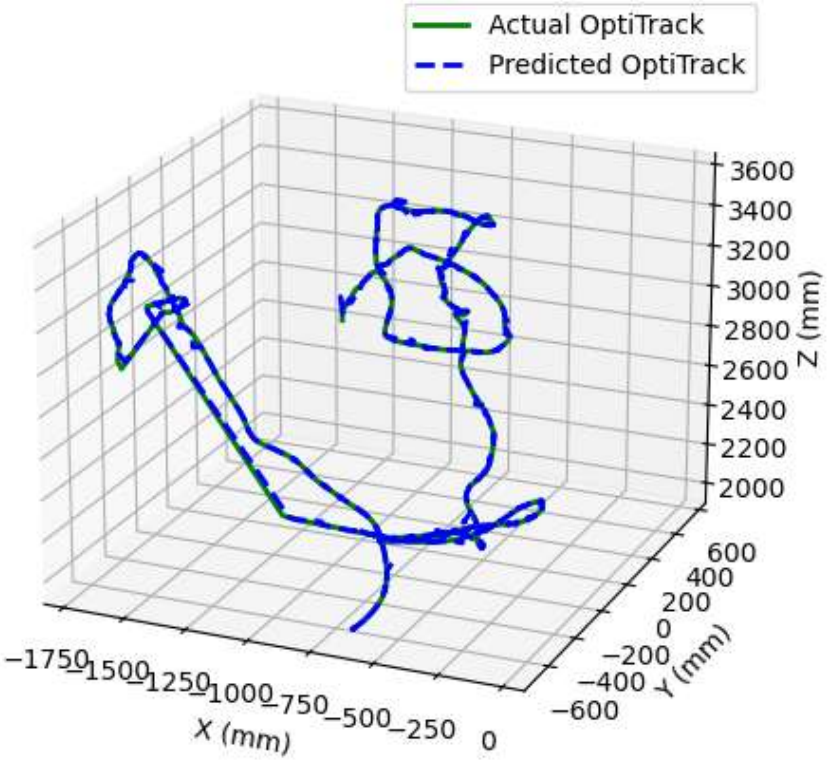
- YOLO annotation software was able to visually show correct bounding box placement throughout the UAV flight.
- Confidence threshold of 25% and intersection-over-union value of 0.1 allowed for most accurate data collection.
- Average differences between YOLO and manually-marked coordinates of the UAV flight were -5.840, 3.744, and 3.534 px in the X, Y, and Z directions, respectively

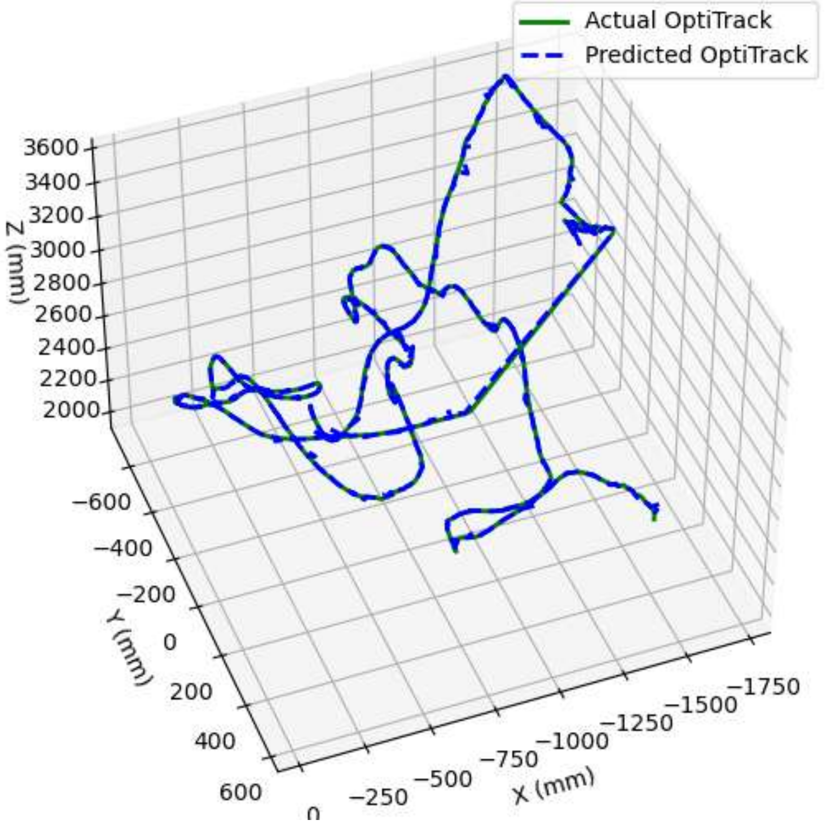




Spatial coordinate prediction using non-linear regression models

- Evaluated models: polynomial regression, random forest regression, support vector regression, gradient boosting regression.
- OptiTrack 3D coordinates are predicted from 3D pixel coordinates using the ML algorithm.
- Support Vector Regression (SVR) model has the best performance.





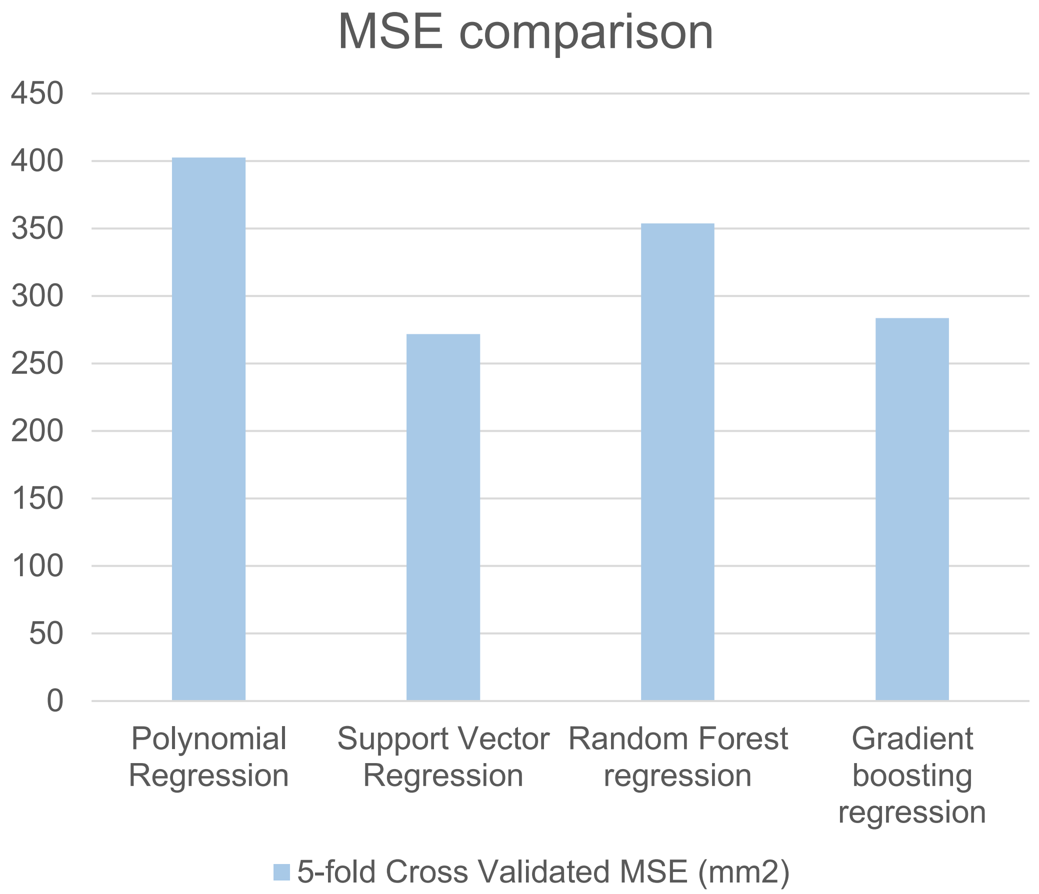
Results

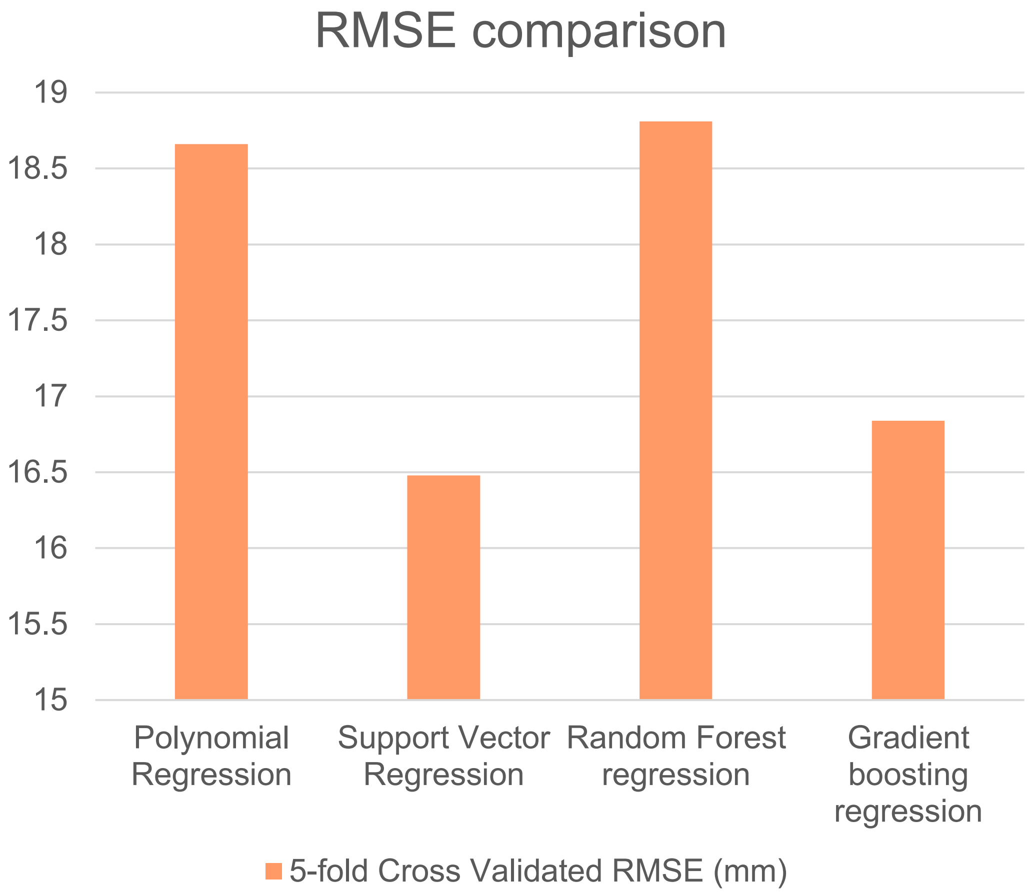
- Performance evaluations for various ML regression algorithms training

Model	Hyper-parameter 1	Hyper-parameter 1 value	Hyper-parameter 2	Hyper-parameter 2 value	5-fold Cross Validated MSE (mm^2)	5-fold Cross Validated RMSE (mm)
Polynomial regression	Number of degree	6	Ridge regularization (α)	1e-5	402.67	18.66
Support Vector Regression (RBF kernel)	Regularization strength (C)	1e5	Kernel width(γ)	1	271.82	16.48
Random Forest regression	Maximum depth	20	Number of trees	350	353.82	18.81
Gradient boosting regression	Maximum depth	4	Number of trees	350	283.73	16.84

Results

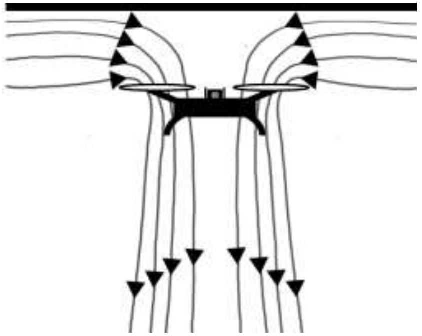
- Performance evaluations for various ML regression algorithms training

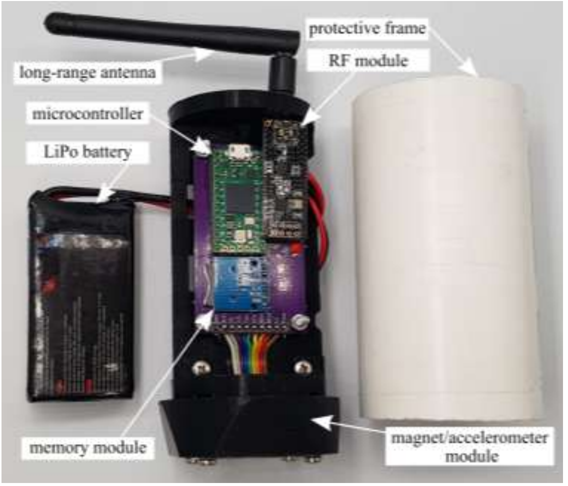


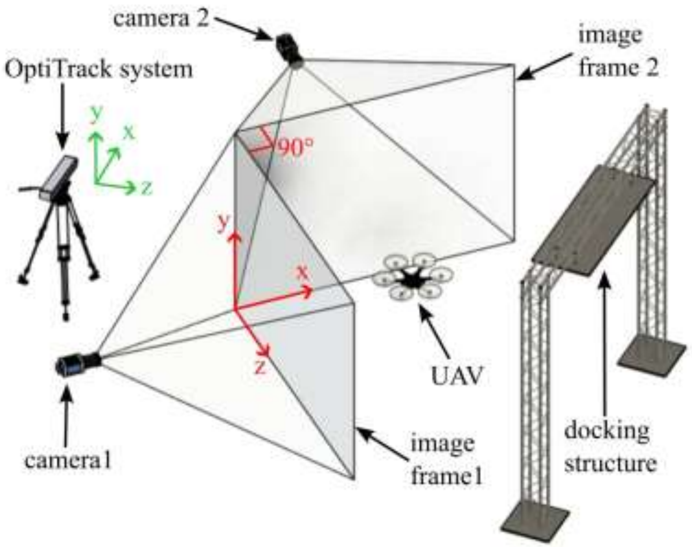


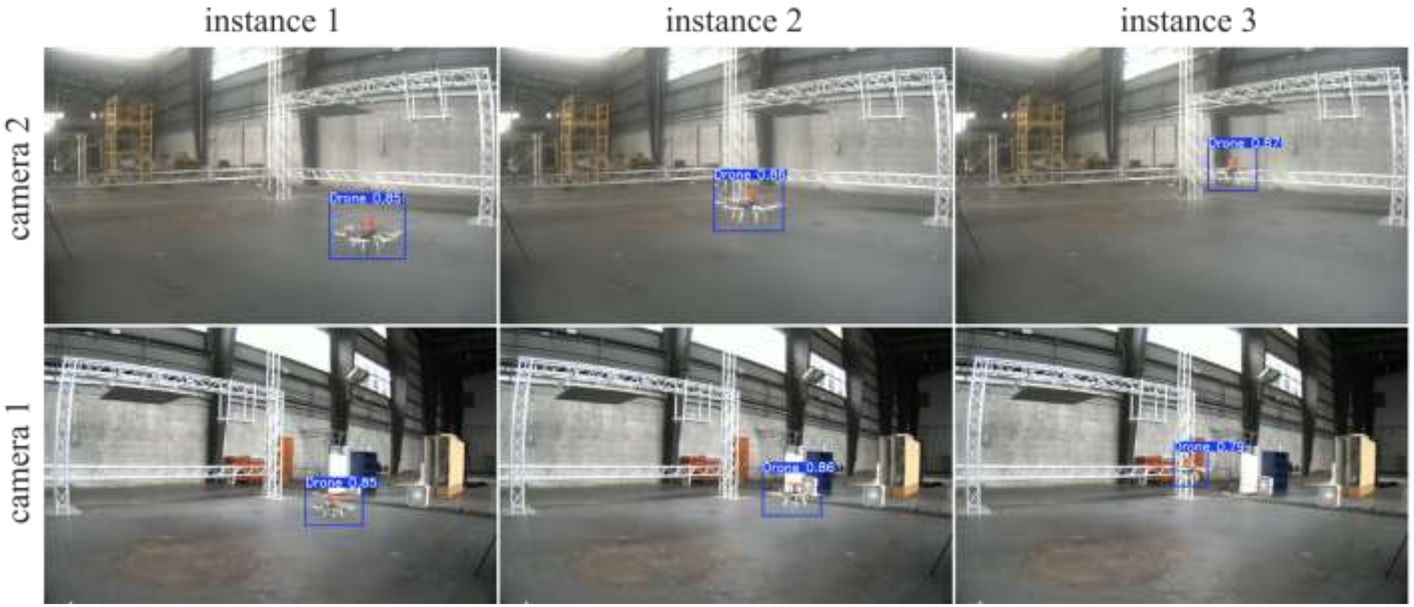
Conclusions

- UAV sensor placement
- Ceiling effect
- Spatial ML
- Object tracking









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https://github.com/ARTS-Laboratory/Paper-2026-Machine-learning-based-UAV-localization

Thanks for listening!

Questions?

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