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Vision-Based UAV Localization Using a Fisheye Ground-Camera Network for Sensor Package Deployment in Post-Disaster Structure Inspection

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Outline

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2. UAV system and test site
3. Methodology
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    2. ML based localization
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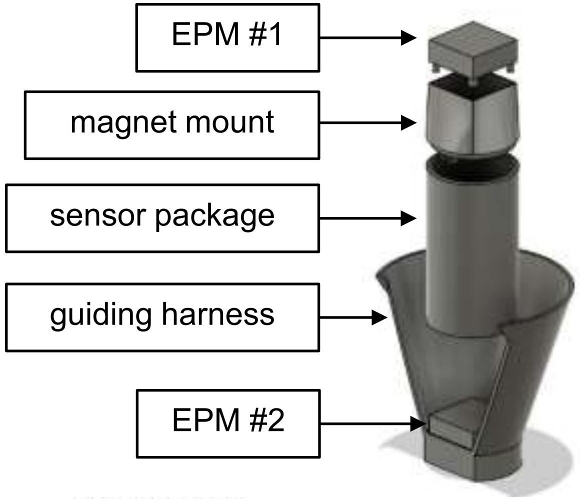
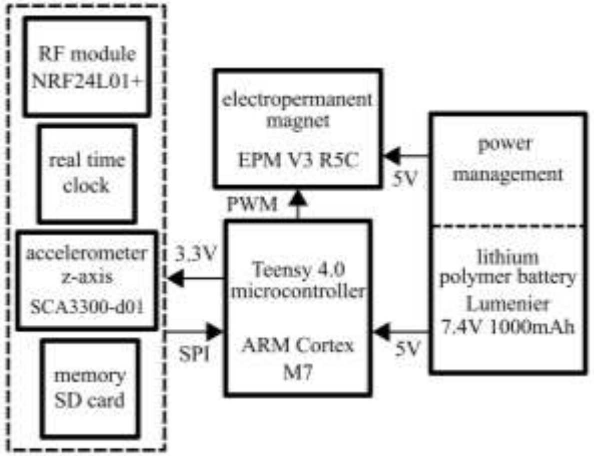
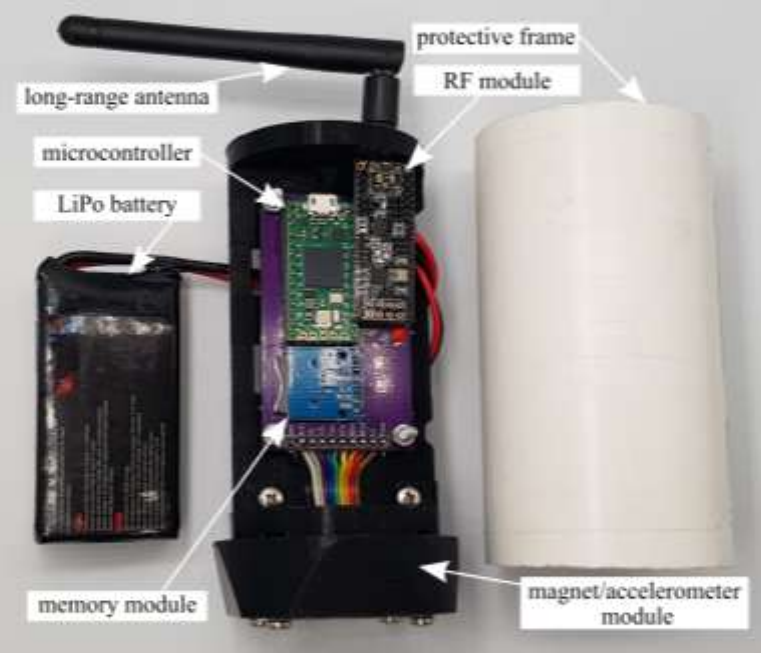
Background

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.

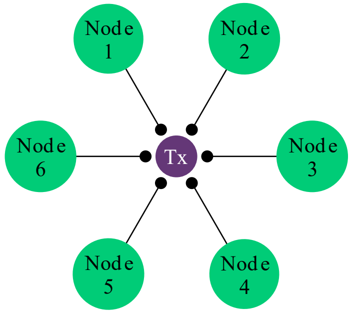


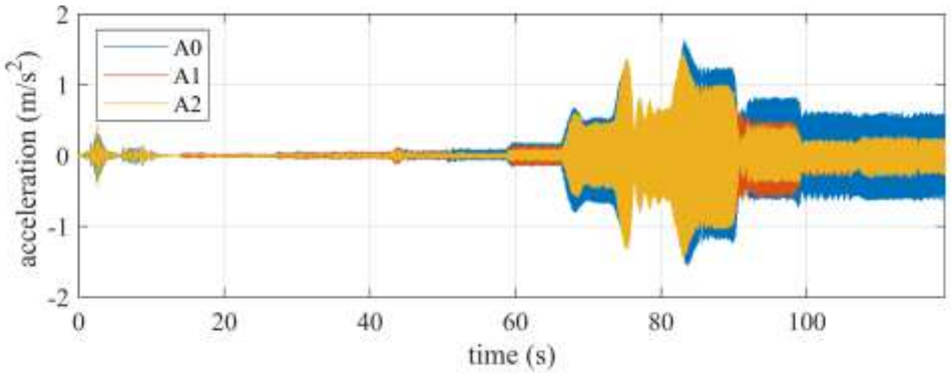


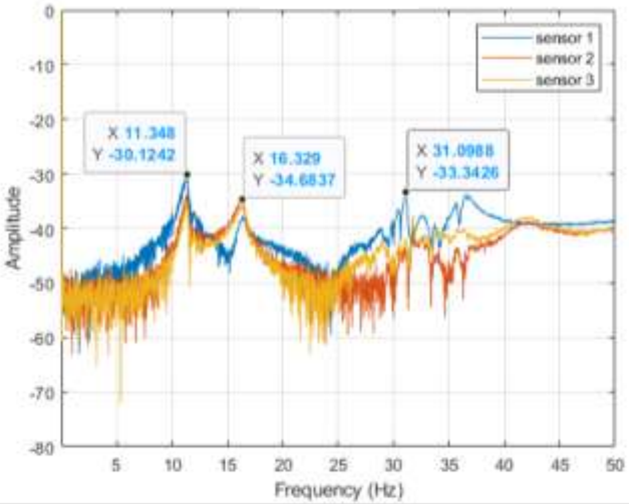


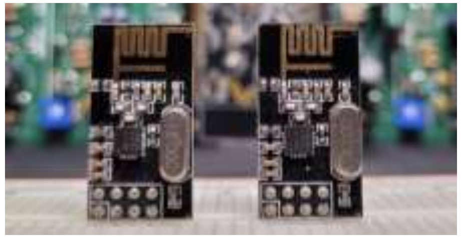
Wireless sensing networks

- 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 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



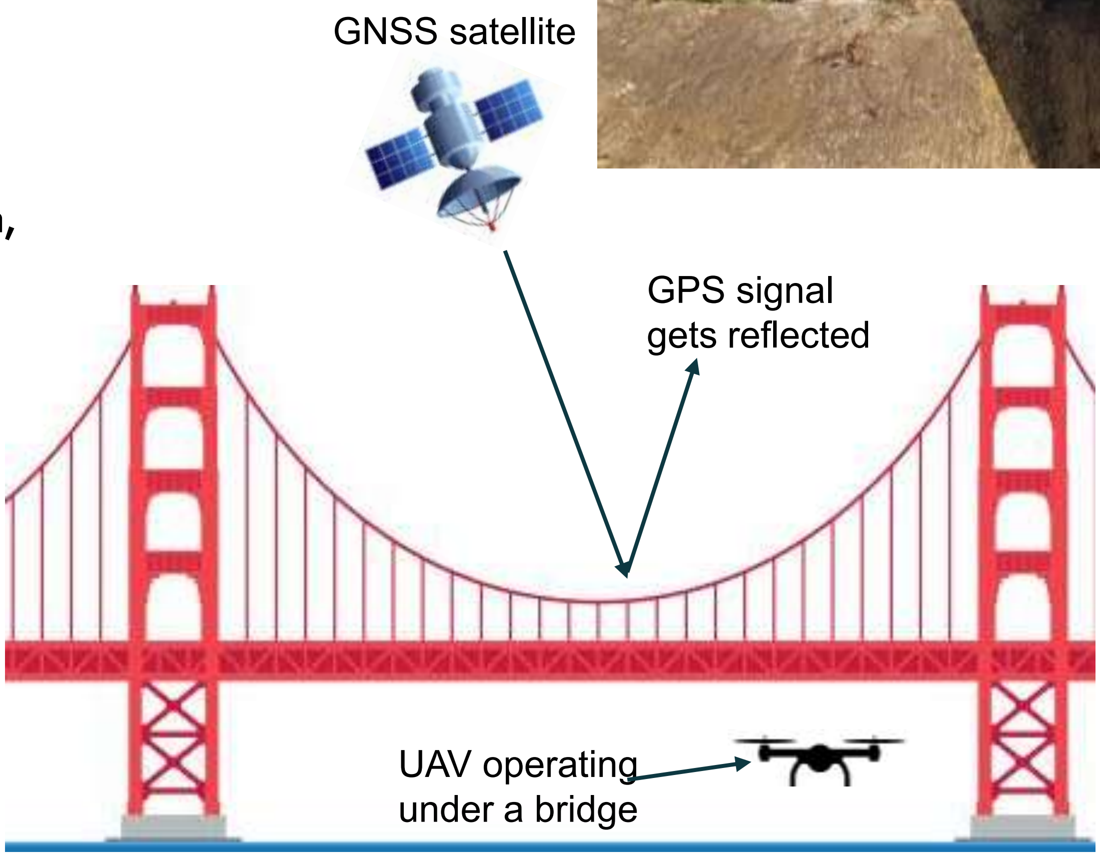






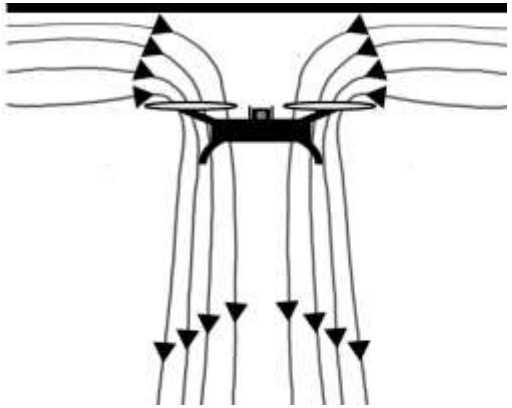
Line-of-sight and GPS signal

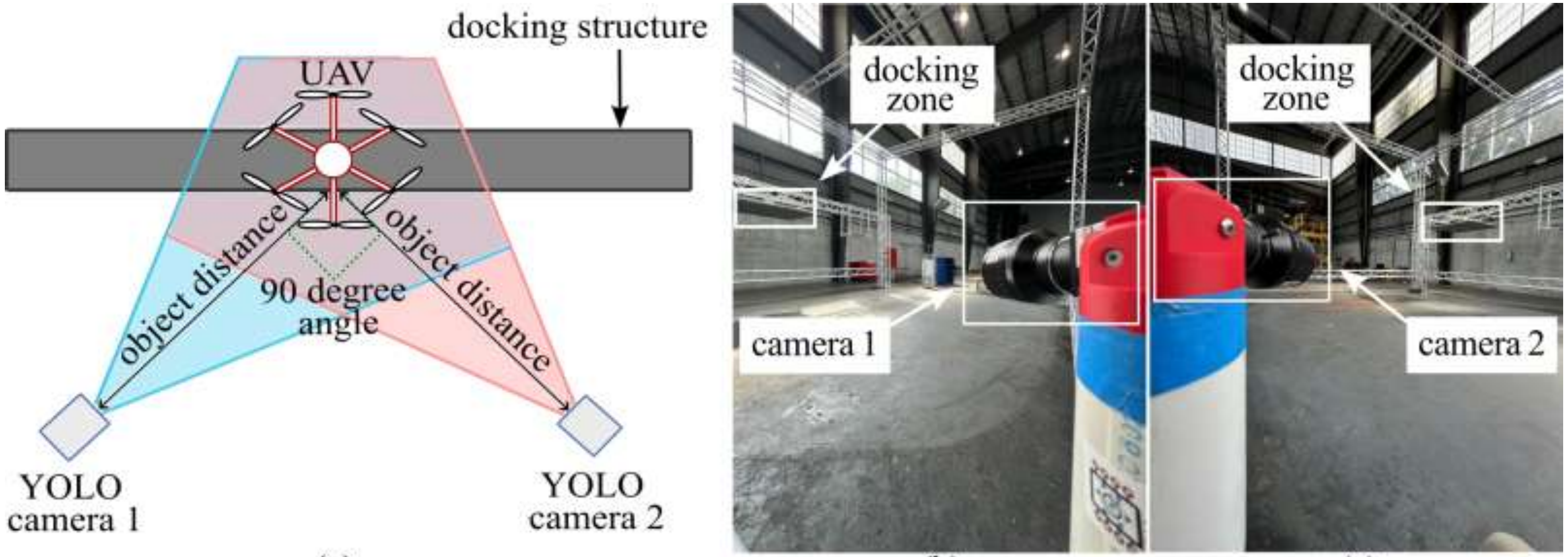
- UAVs are often manually piloted under structures to place sensors for analysis.
- Placement via manual control often leads to imprecise navigation during deployment.
- Line-of-sight issues complicate UAV navigation, as explained in the video on right.
- GPS signals near large metal structures (or indoors) 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.

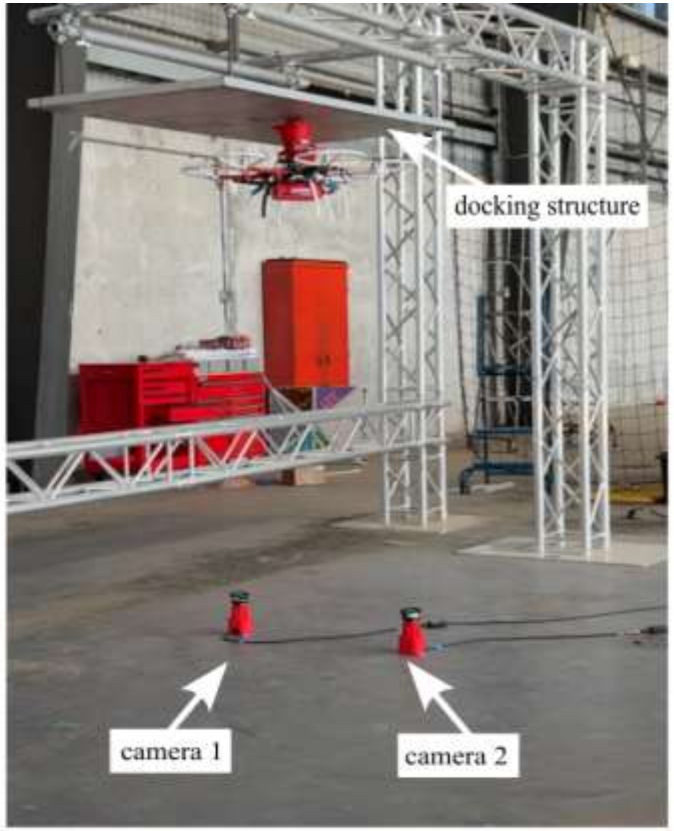


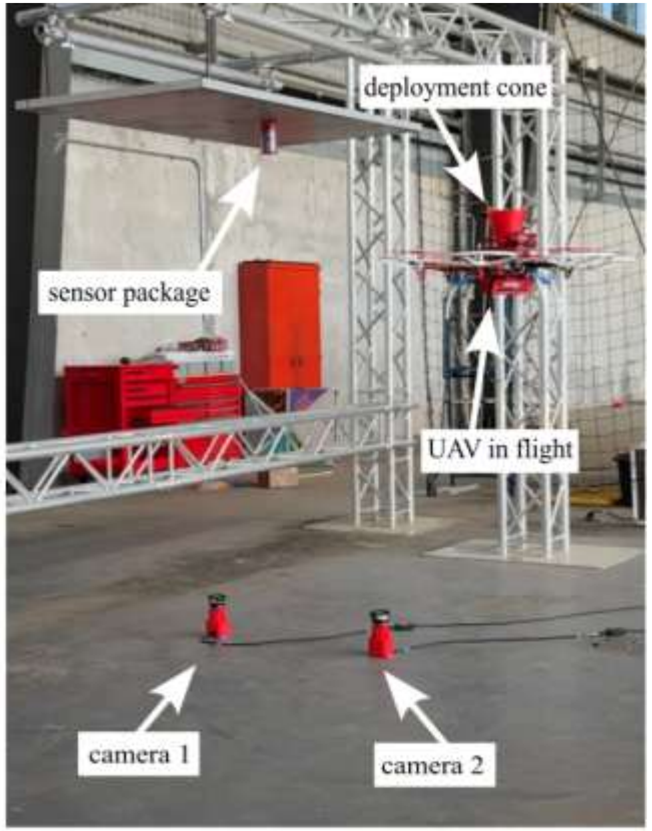


(a) (b) (c)

UAV system test site and technical aspects

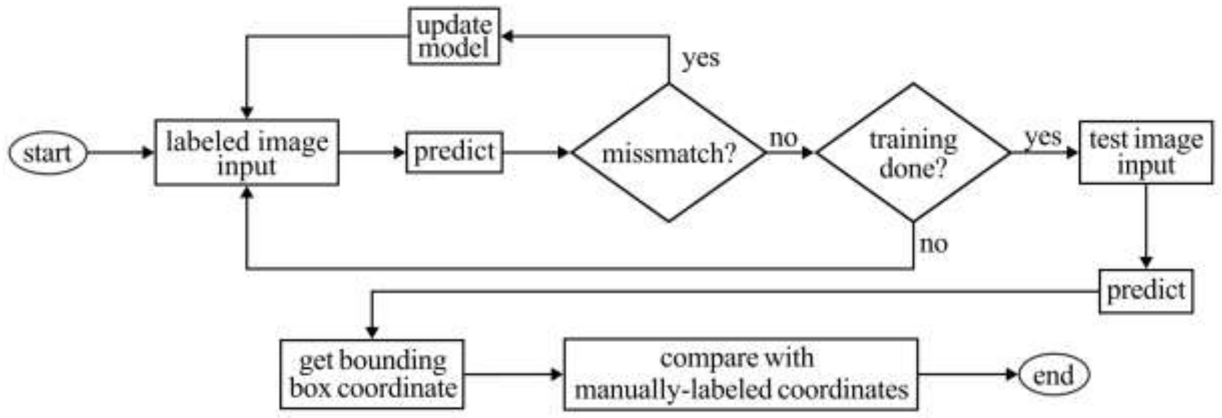
- Utilizes a metallic structure, UAV, and sensor package. Metallic structure consists of three large beams with a horizontal "docking zone".
- The UAV is equipped with an electro-permanent magnet-based sensor deployment mechanism.
- Two 6 mm focal length monochrome-cameras were positioned at a 90° angle facing the structural docking zone (ferrous at the bottom of the central axis facing metal plate 152.3 x 152.3 cm in length/width)
- Cameras were positioned on upright-facing mounts, with one camera placed directly under the docking zone, and a separate camera placed 0.72 m from the center camera. Cameras were mounted 0.14 m from ground level.

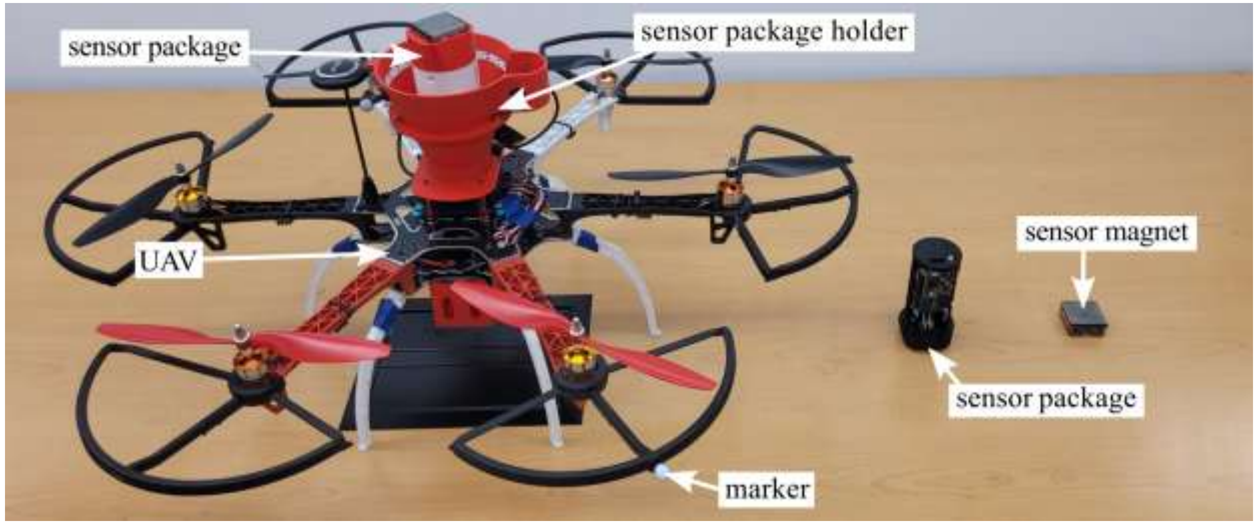




UAV recognition with You Only Look Once (YOLO)

- 127 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
- 46-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"





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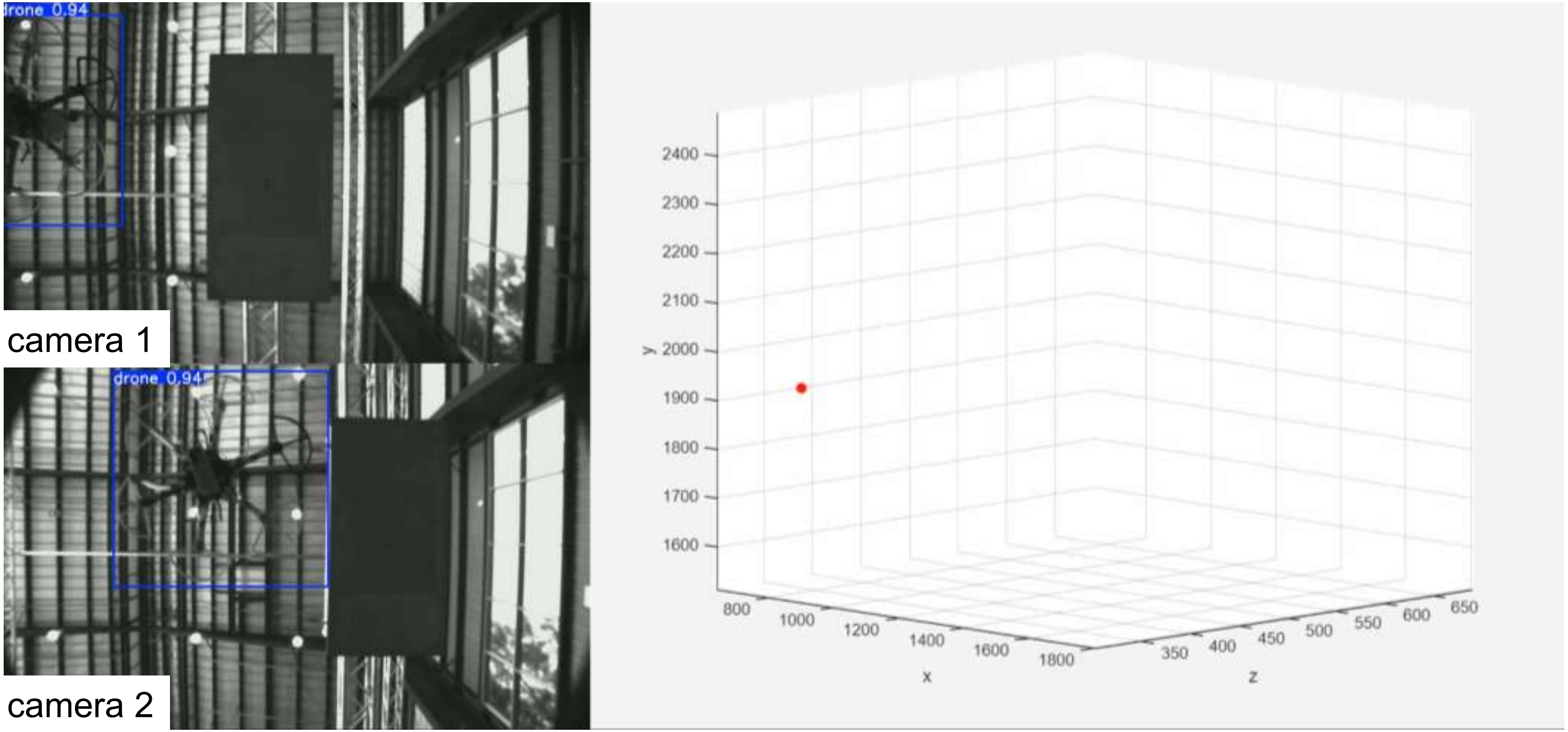
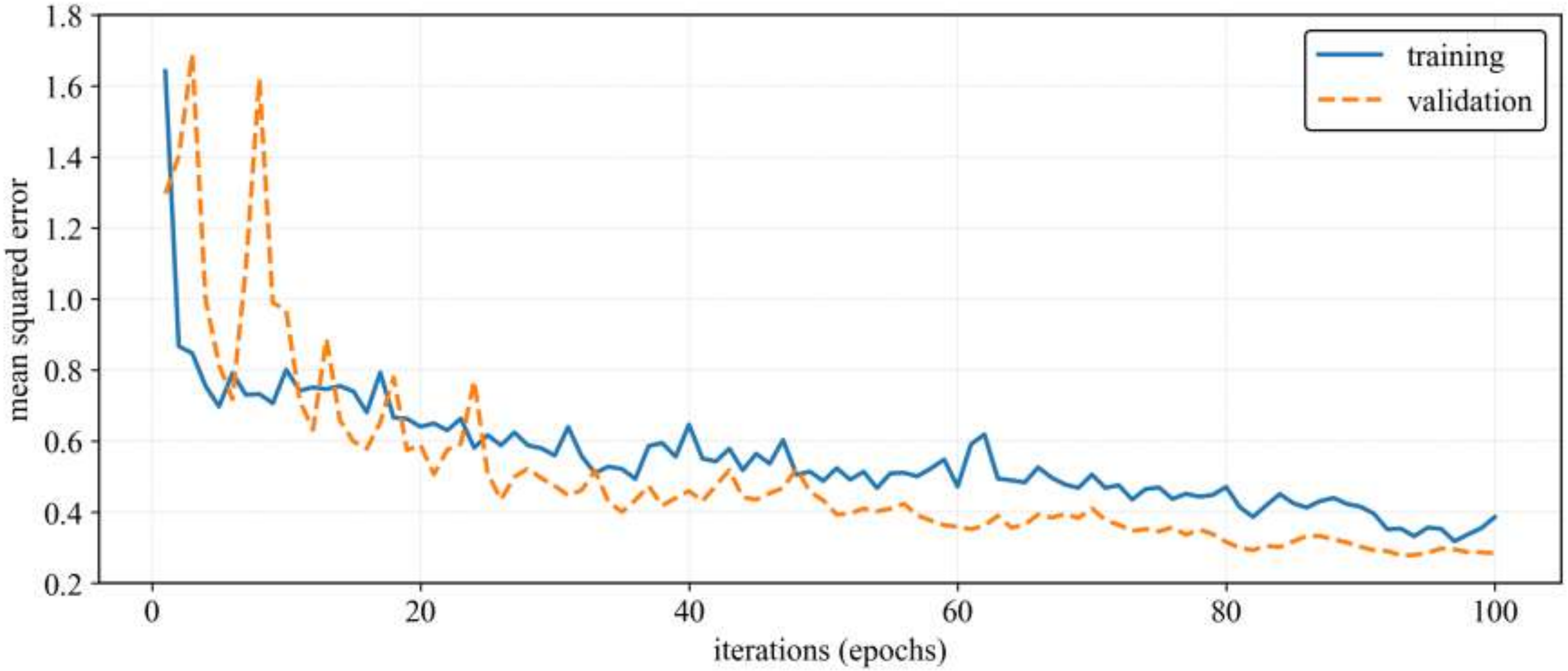


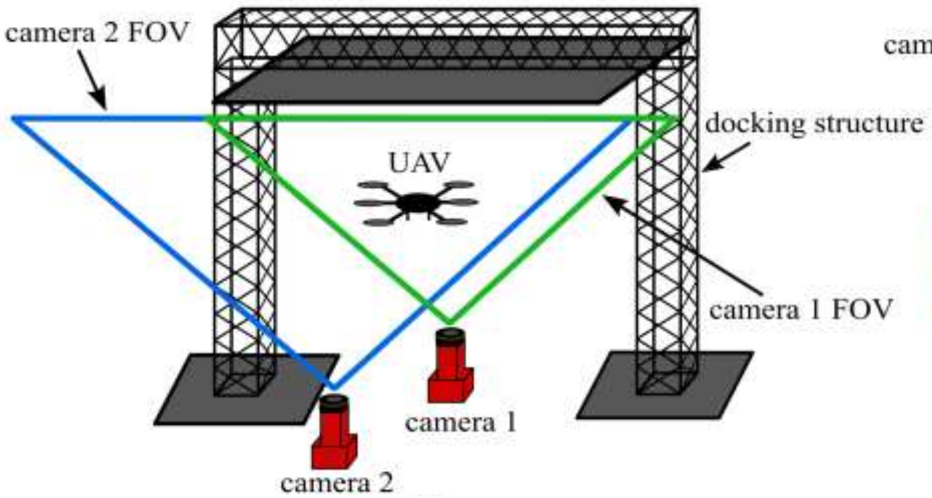
UAV recognition with You Only Look Once (YOLO)

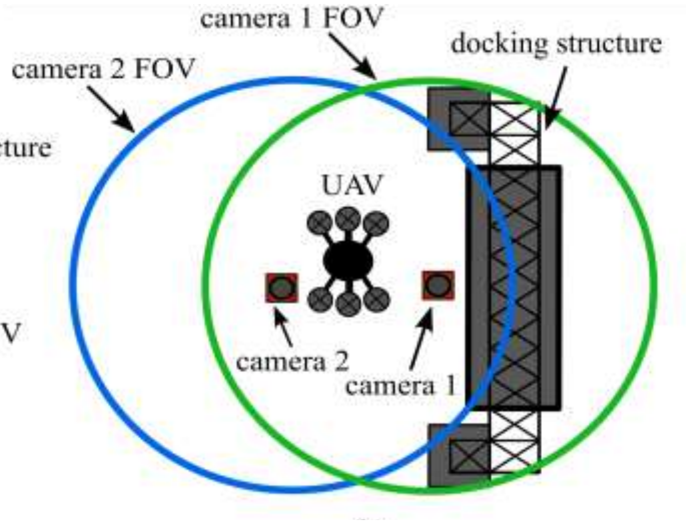
- Final YOLO model had a training box loss of 0.40 sq px and a validation box loss of 0.30 sq px by 100 epochs
- Validation errors showed more stability with more epochs, while training errors showed continual improvements
- Machine-learning-based tracking systems can be readily developed to provide accurate positional data of UAV sensor docking

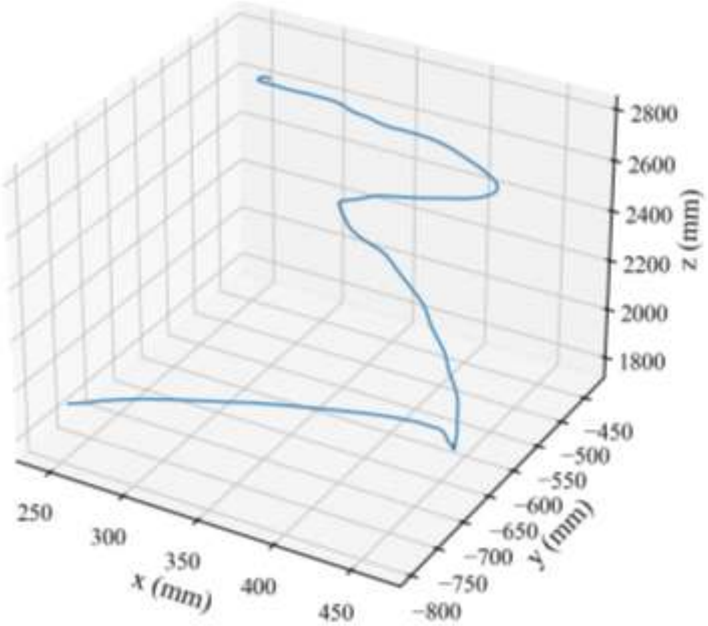


Creating 3-dimensional spatial coordinates with ground truth

- 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.

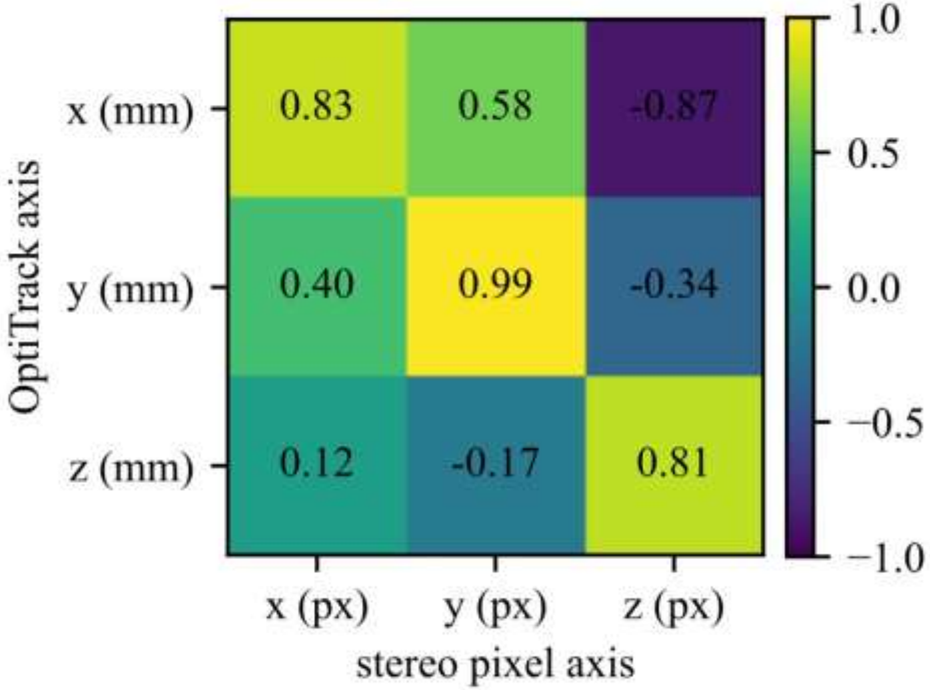


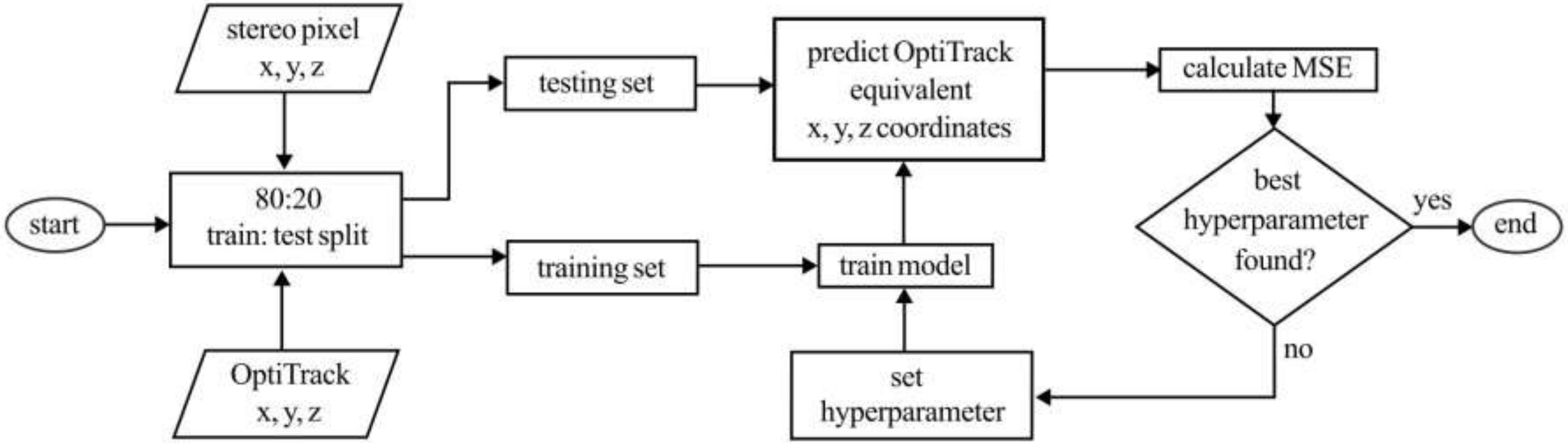




Tracking system linearity

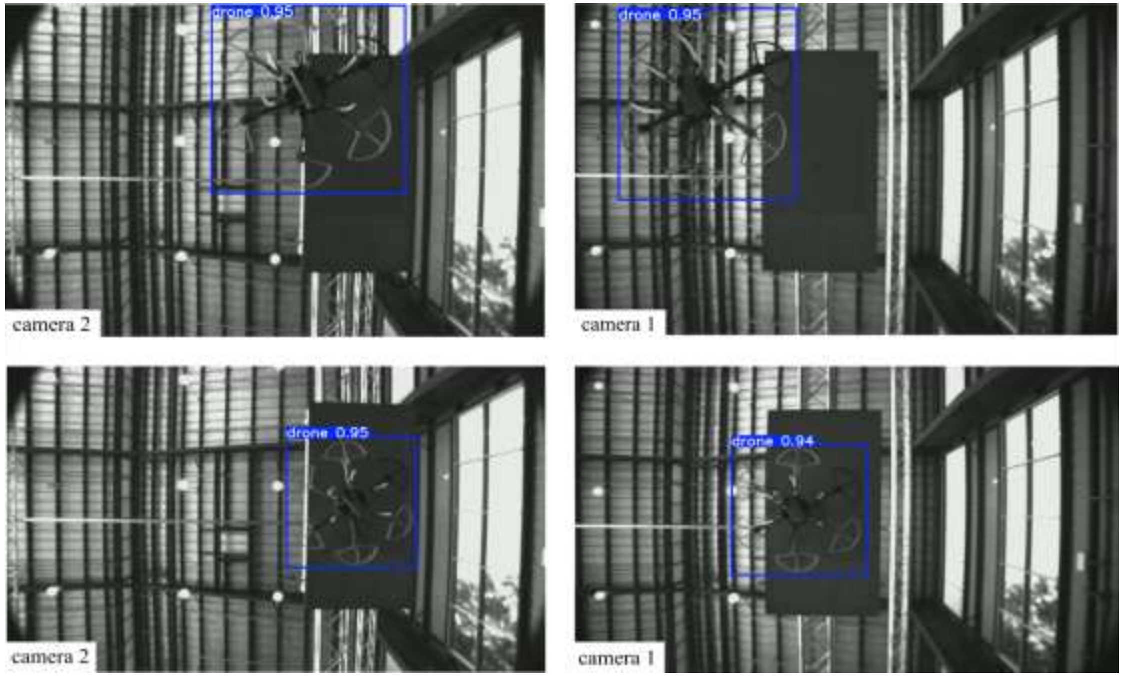
- The Pearson correlation matrix shows that pixel-based YOLO coordinates are not linear with their spatial distance coordinates.

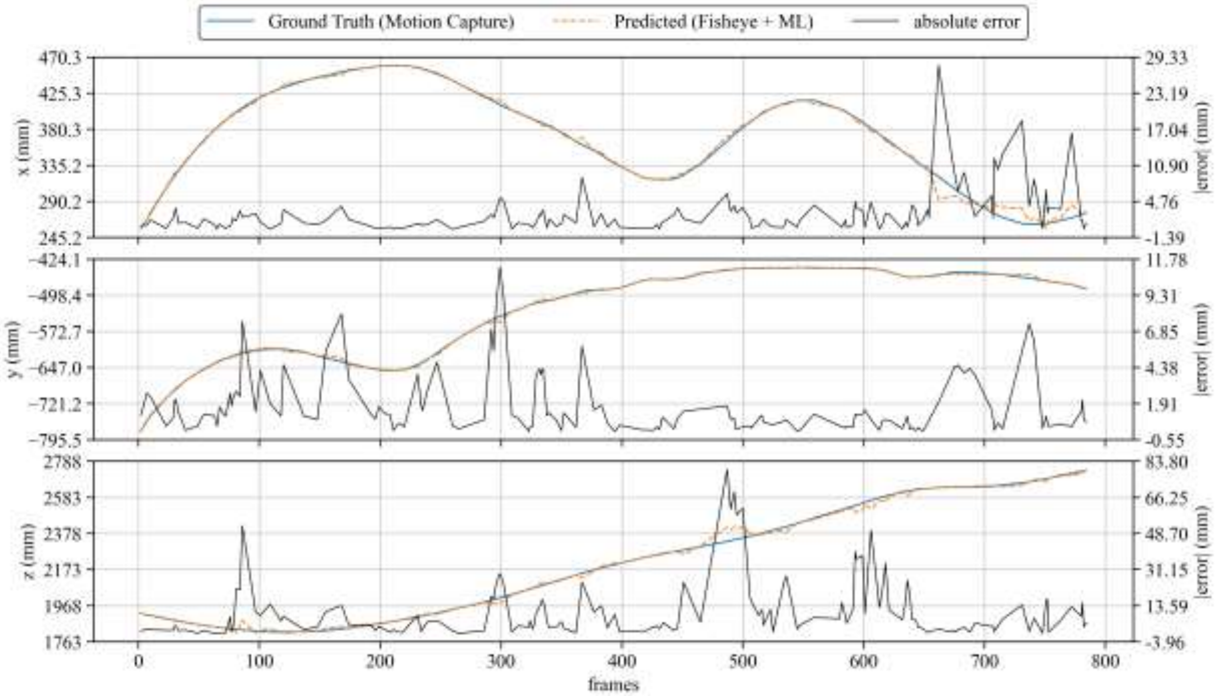




Results

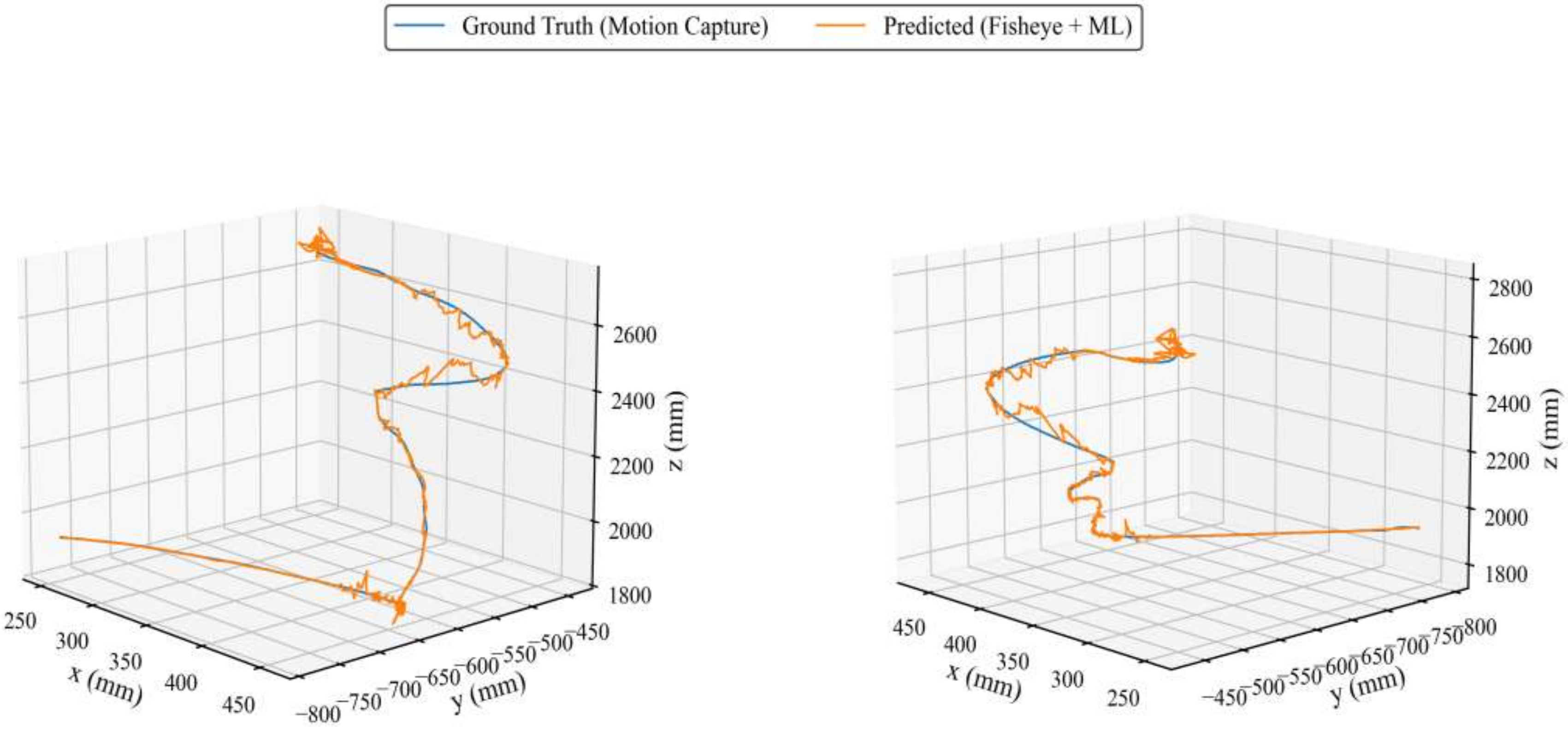
- YOLO annotation software was able to visually show correct bounding box placement throughout the UAV flight.
- 20% of the data was used to evaluate the SVR model, with 80% of the data going into training.
- RMSE of approximately 10.81 mm across the plot, with occasional spikes in error.





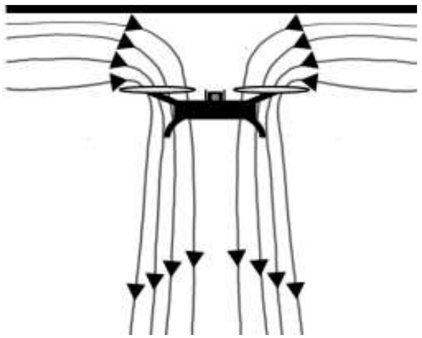
Spatial coordinate prediction using non-linear regression models

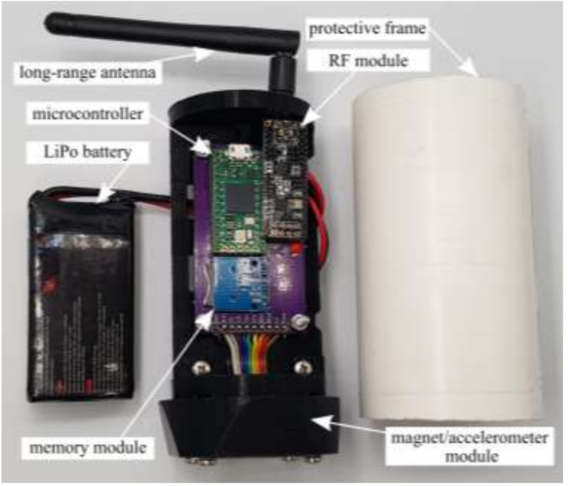
- Evaluated models: polynomial regression, random forest regression, support vector regression, gradient boosting regression.
- OptiTrack 3D coordinates are predicted from 3D pixel coordinates using the ML algorithm.
- Support Vector Regression (SVR) model has the best performance.

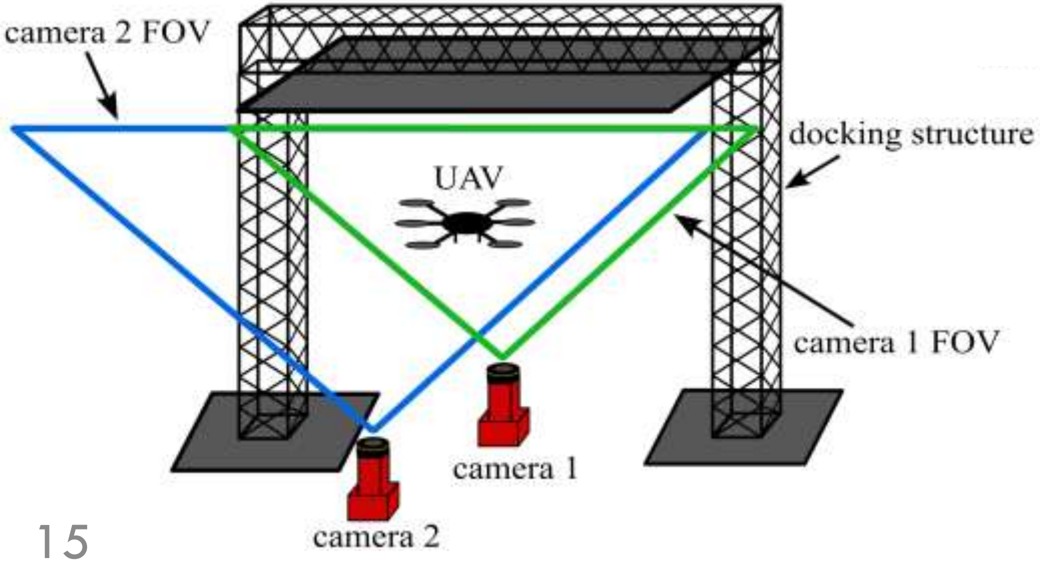


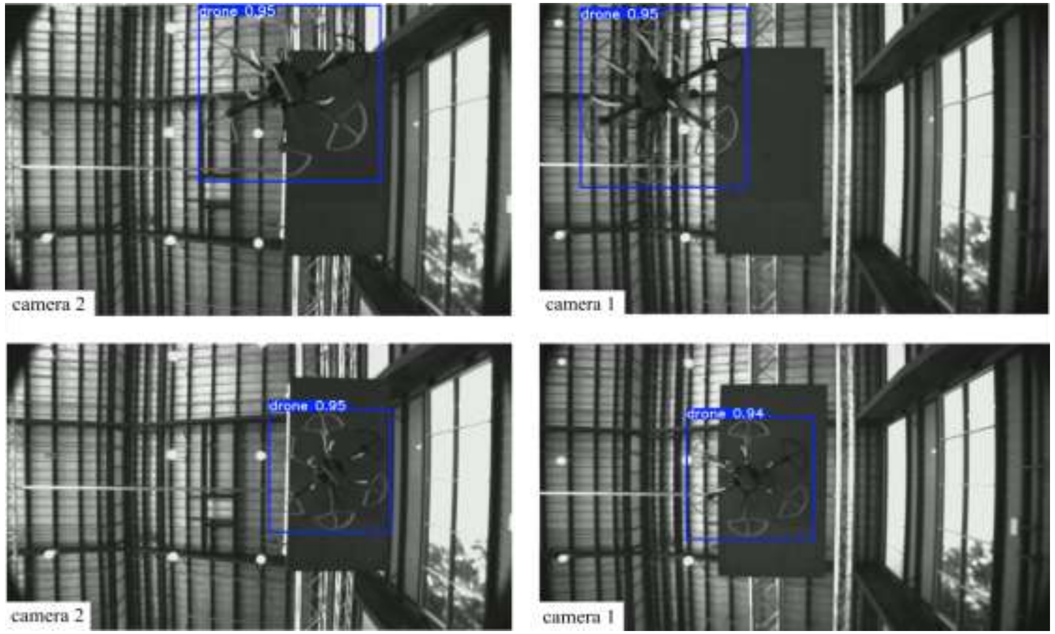
Conclusions

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









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https://github.com/ARTS-Laboratory/paper-2026-fisheye-ground-camera-network-UAV-localization

Thanks for listening!

Questions?

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