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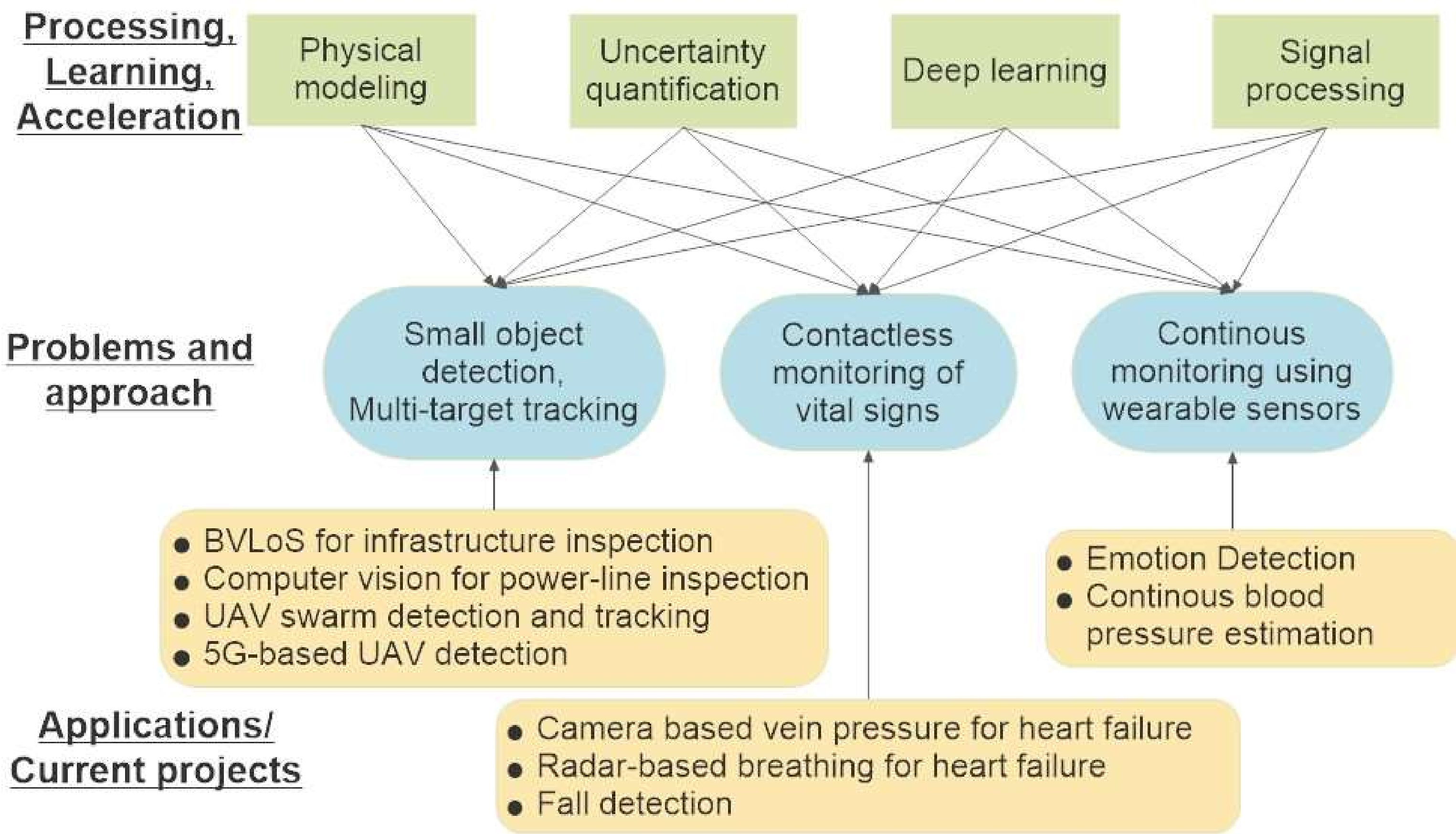
METHODS FOR UAV DETECTION

July 30, 2024

Outline

- **Introduction**
  - Our group at UOttawa
  - Counter UAV systems
- Our work on Counter UAV
  - Object detection
  - Distance estimation
  - Payload detection
  - Multitarget tracking
  - Intent modeling
- Resilient AI and future works
  - What is resilient AI
  - Directions in Counter UAV field with resilient AI

Computational Analysis and Acceleration (CARG) Research Group



Motivation for Counter UAV systems

Technological

- Proliferation of UAVs
  - Increasing use in civilian and military sectors
  - Applications include delivery services, surveillance, and agriculture
- Technological Advancements
  - Rapid evolution in UAV capabilities requires equally advanced countermeasures
  - Development of sophisticated detection and response technologies

Defence and Security

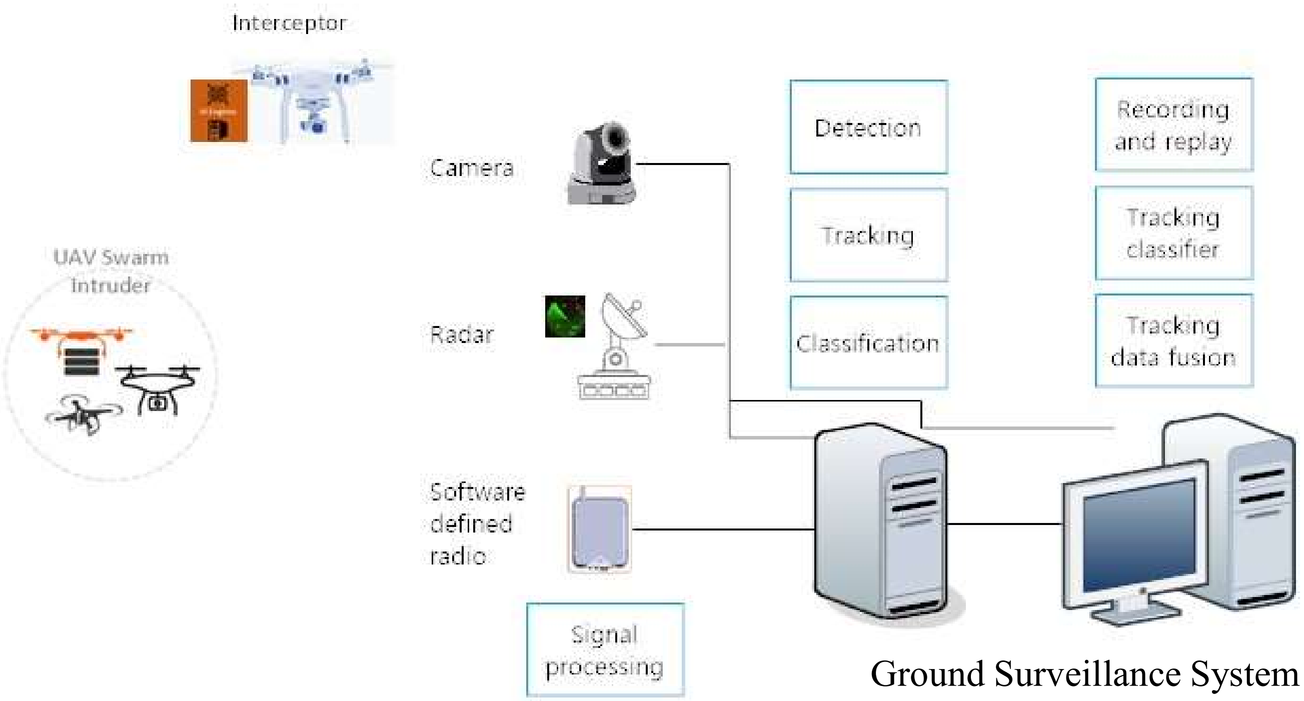
- National Defense and Counter-Terrorism
  - UAVs pose a threat in asymmetric warfare and terrorism
  - Essential to detect and neutralize hostile UAVs quickly
- Security and Privacy Concerns
  - Potential threats to privacy and security from unauthorized UAVs
  - Risk of UAVs being used for malicious activities, such as spying or smuggling
- Airspace Safety
  - Prevention of collisions and interference with manned aircraft

Counter UAV systems and our focus

- **Detection, identification, tracking** and neutralization of unauthorized or hostile UAV systems
- Detection includes processing sensor signals (camera, radar, RF, acoustic) from both ground and airborne sensors to detect a new object
- Identification includes classification of the detected object as a UAV
- Tracking includes prediction of the UAV's trajectory

- There are also other topics not covered in traditional Counter UAV systems that we work on:
  - Resilience in AI
  - Payload detection and classification

Counter UAV Detection: System Architecture

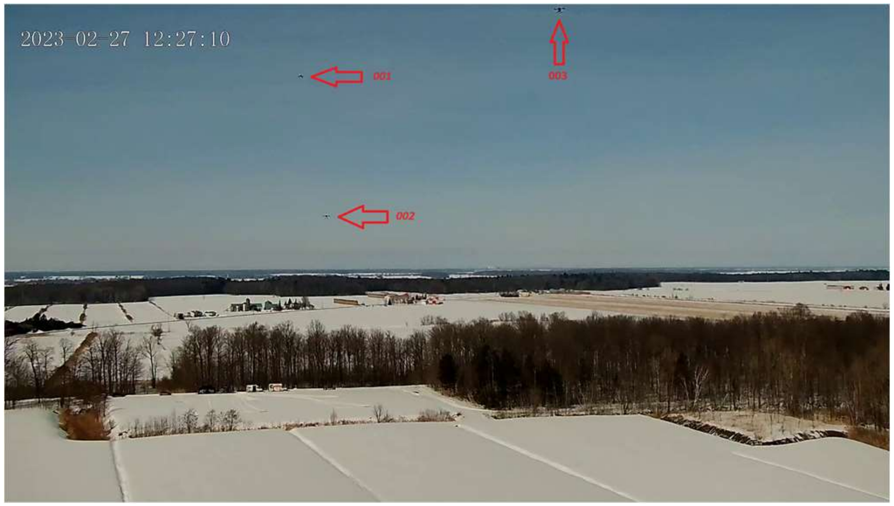


Operation of the system:

1. Ground Radar and PTZ camera serve as early warning sensors to detect the swarm.
2. The mission operator confirms the alert and initiates interceptor UAV flight towards the detected UAVs.
3. Interceptor UAV performs detection, tracking and payload classification.
4. Ground Surveillance System runs AI models for sensor fusion and swarm characterization.
5. UAV tracking data and swarm information are continually presented to the operator.

What are difficult problems for Counter UAV systems?

- Detecting and classifying objects at large distances
- Detecting objects in front of dark or unknown backgrounds
- Making sure that machine learning models do not break when encountering unseen data/environments
- Multi-sensor fusion especially when fusing airborne and ground sensors
- Complex processing with limited resources



Real data collected in 2023 by CARG showing three intruder UAVs observed via an EO sensor on an interceptor UAV. This highlights the need to approach intruder UAVs closely for improved observation and payload classification.

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Object detection using cameras

Challenges

Object detection
- Small object detection using computer vision
- Domain shift in object detection

Data collection
- Difficulties in conducting experiments
- Difficulties in synchronizing data from multiple sensors and labelling data

Real-time implementation
- In the ground control
- In the UAV

Approach

- Using modern deep learning object detection models such as YOLO
- Using Kalman filter-based trackers for post processing (deep Sort)
- Developing our own dataset for domain shift problems

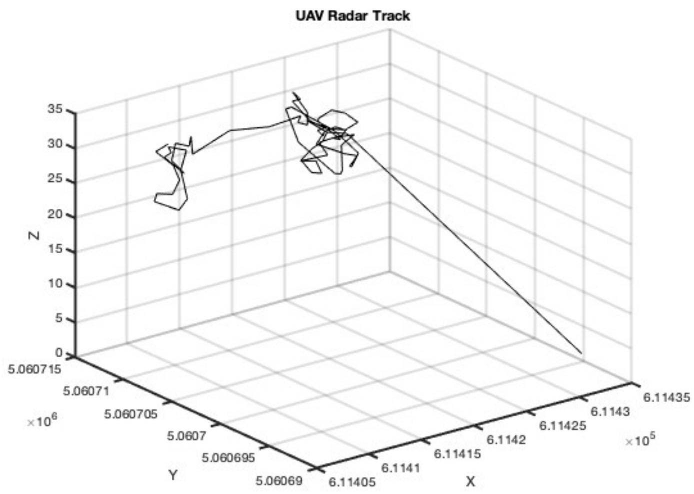
Object classification using radars

Challenges

- The UAV small radar cross section makes the detection challenging.
- The goal is to classify UAVs at the distances >500 m when they appear as point targets
- Classes: UAVs, birds, cars, other

Collected data

- Total no of tracks: 4161 (with 50 samples window length)
- Total UAV tracks: 2732
- Total Bird tracks: 917
- Total other tracks (Real + Synthetic): 512



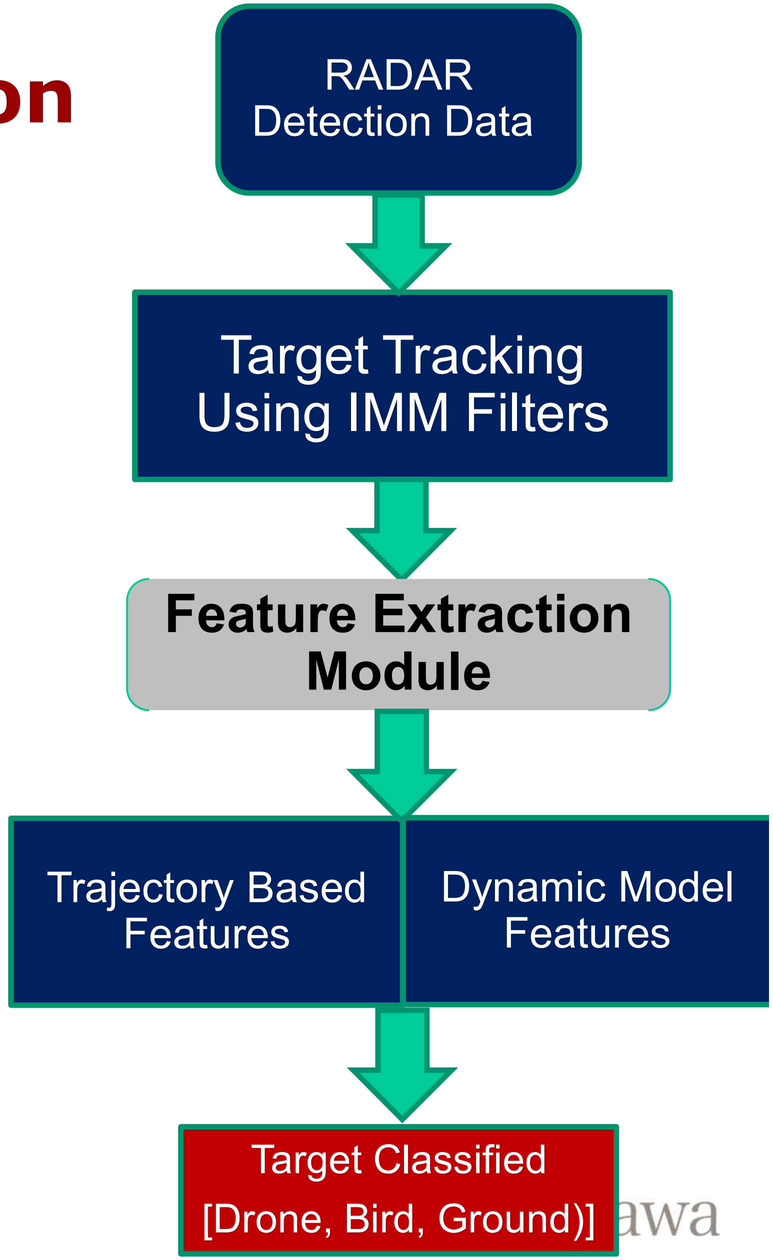
Features and classification model

Approach

- Using Interactive multiple models (IMM) with Extended Kalman Filters to determine the motion pattern
- Extract features from the model
  - Trajectory-based : Mean and Variance of Curvature, Slope, Jerk, Radial Velocity and Acceleration
  - Dynamic features: Mean and Variance of velocity and acceleration along x, y and z axis, model probabilities

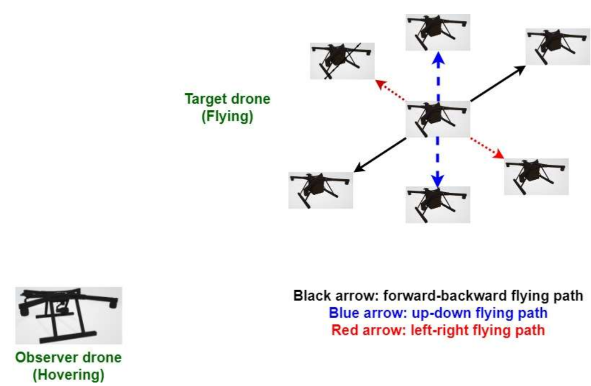
Results

- High accuracy in classifying UAVs (>90%) but lower in classifying birds



Payload detection using videos

- **Main objective**: classify the target drone into one of two classes (loaded or unloaded) using the recorded videos/images
- **Using experimental and simulation dataset**
  - A quadrotor drone in both loaded and unloaded cases as the target
  - Another quadrotor drone equipped with a camera to capture images of target drone
    - FoV of 62.7 degree, resolution 1080*1920 pixels
    - 30 frames per second
  - Air-to-air setup
    - Target distances ranging from 20 to approximately 100 meters from the camera
- **Accuracy > 90%**



Video-based distance estimation

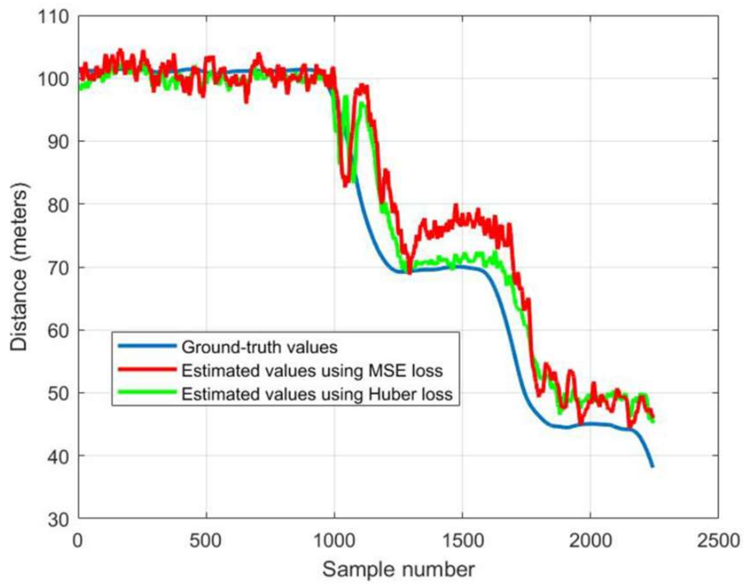
Single-camera based localization

- It is important to know how far the object is for:
  - Collision avoidance
  - Association algorithms for fusion
- Challenges of using video-based localization:
  - Unknown objects
  - Oriented drone
  - Distance estimation in the case of the partly captured image of the drone
  - Uncertainty in labels

Distance estimation results

Single-camera based localization

- Input to the network
    - Bounding box images
    - Width and height of the bounding box in pixels.
- Trained both with simulated and experimental data
- Future directions
    - Including uncertainty in labels due to GPS errors in the model
    - Performing localization fusion after the association is done
    - Applying Kalman/particle filter to smooth the results

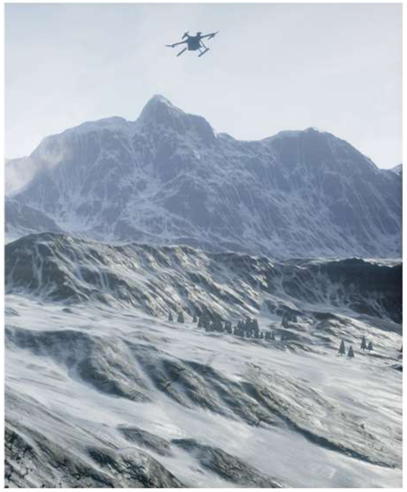


Multitarget tracking

- **Sensor fusion**
- **Association between different sensors and targets to come up with unique IDs**
- **Multi-view drone localization**
  - More than one observer drone with a camera

Cam 1

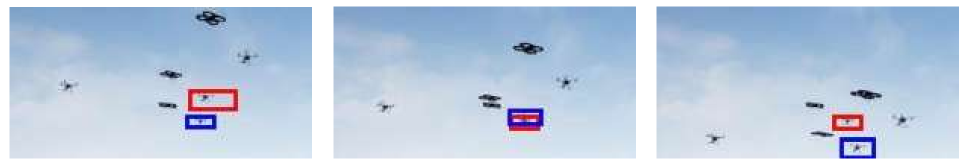
Cam 2



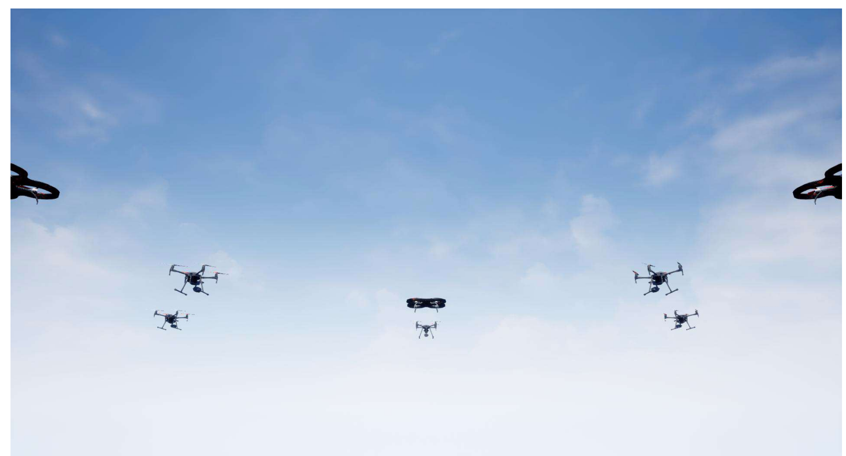
Association with the ground camera and radar

Computer vision + radar fusion

- Traditional methods failed
  - Similarities in UAV appearance
- Deep learning approaches
  - High accuracy in tracking and association for simulated cases
  - Based on position and velocity similarity scores between different bounding boxes
- Research directions
  - Improve and include appearance modules
  - Focus on multi-camera association
  - Include a realistic radar model



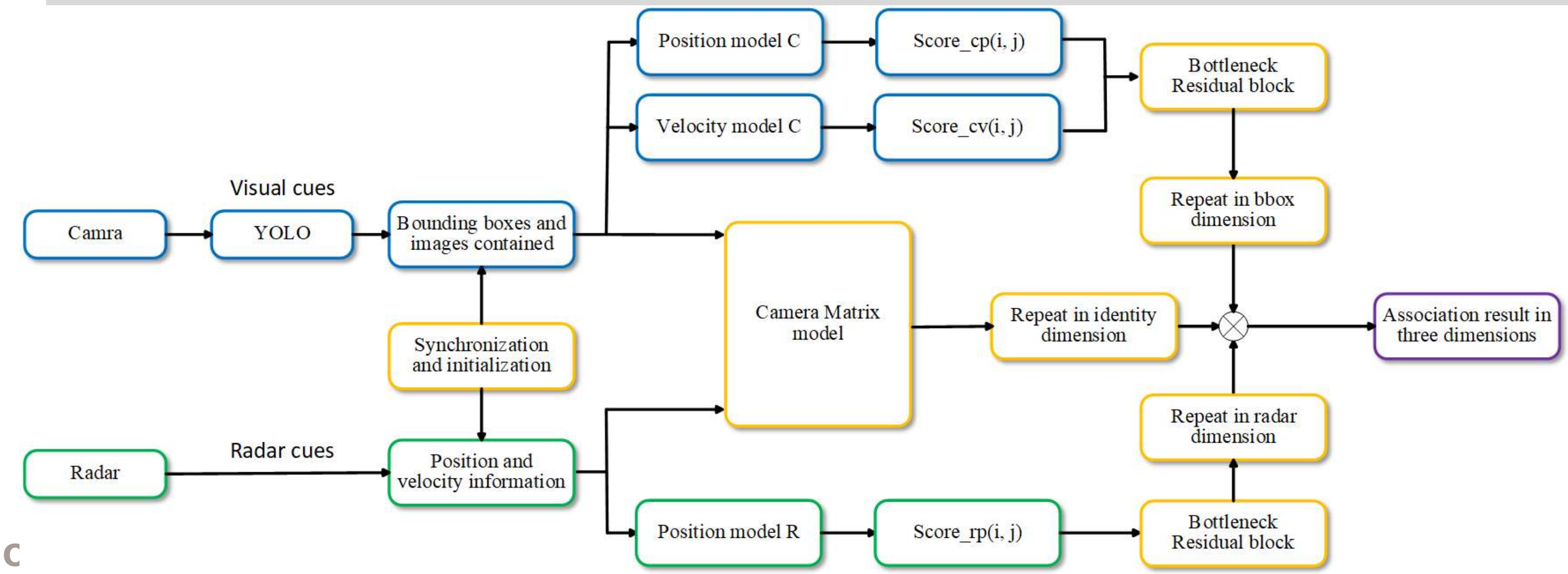
frame t-1 frame t frame t+1



Association: Proposed architecture

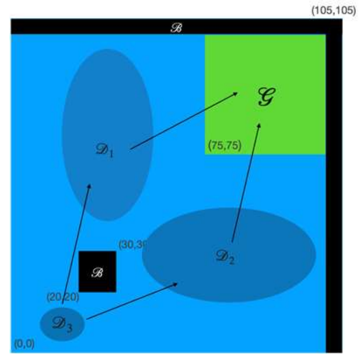
Architecture

- Synchronization and initialization: data preprocessing
- YOLO: bounding box information and ROI images extraction
- Position/Velocity model: LSTM tracker
- Camera Matrix model: MLP-based similarity calculation - higher similarity score means that the radar detection is more likely to belong to a bounding box
- Core fusion: Bottleneck residual block



Intent detection

- The types of intents considered include:
  - reaching a specific destination or entering an area of interest (AoI)
  - library of behaviours based on the application,
    - kamikaze attack, smuggling, dropping objects, image acquisition
  - deviation from expected behaviour.



Intent models and trajectory generations

The library of intents, environments and obstacles → Intent motion patterns using destination and critical waypoints → Motion planning:
- Path finding
- Optimizing trajectory

→ Generate labelled dataset → ML models for intent recognition

uOttawa

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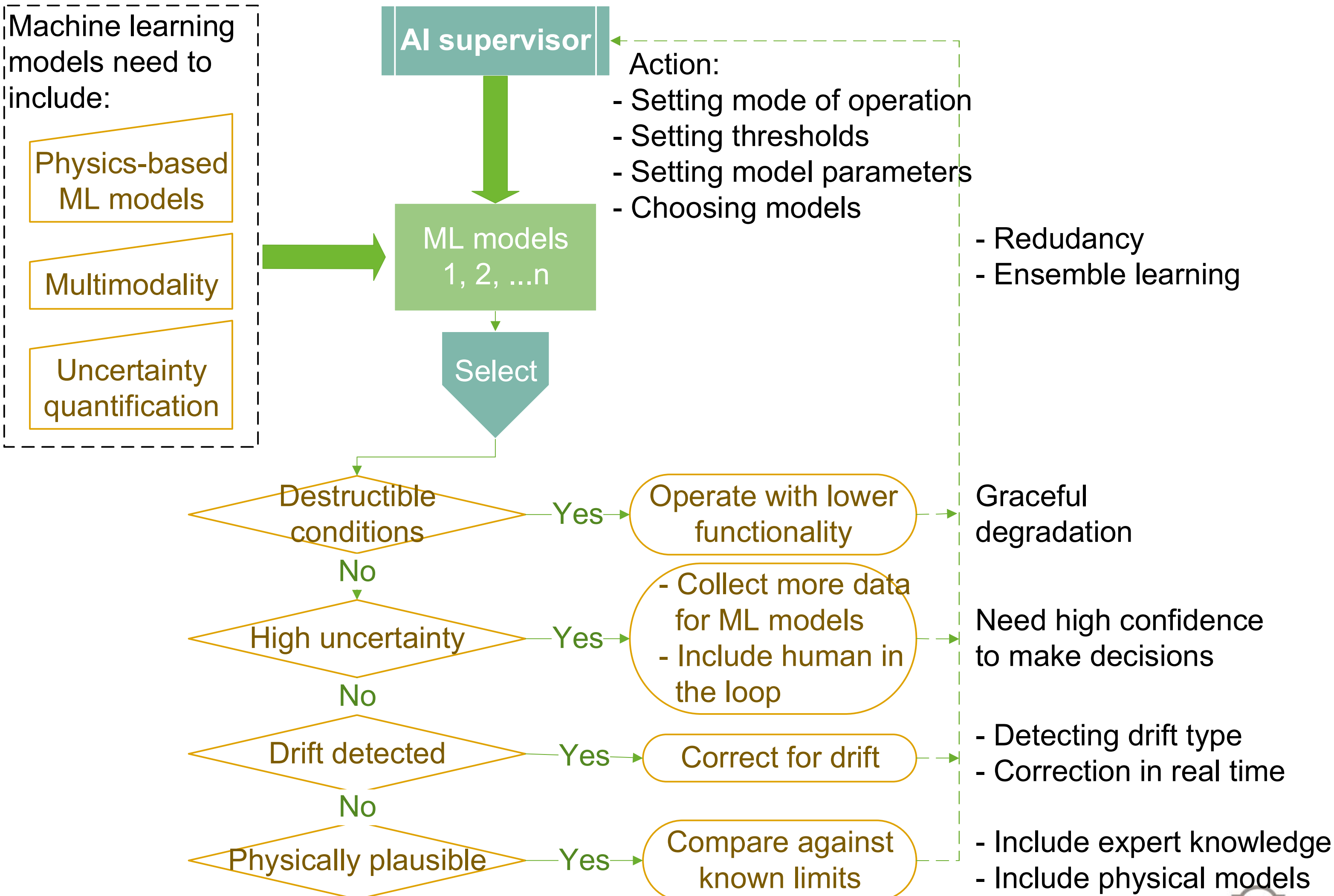
Resilient and Robust AI

- Resilient AI refers to the ability of artificial intelligence systems to maintain robust performance and functionality in the face of various challenges, adversarial conditions, or unexpected events.
- A resilient AI system can adapt, recover, and continue functioning effectively even when confronted with disruptions or uncertainties.
- When deployed in a production environment, an ML model is considered robust if variations of input data, as specified by a domain of potential changes, do not degrade the model's predictive performance below the permitted tolerance level.

AI supervision and monitoring for resilience



Conclusion

Counter UAV Directions

- Detecting concept drift based on a single measurement and reacting on it
- Define metrology metrics for the regression problems and see how to address them
- Follow the development of AI standards
- Building robust AI systems using reinforcement learning and physical modeling
- Building a complex simulator that would allow for modeling different cases and user scenarios

Our other UAV projects

- Beyond visual line of sight flights
- Powerline inspection and classification of powerline components
- Detection of UAVs in 5G networks

Thanks!

CARG UAV Team

- Dr Kesav Kesa, PDF
- Dr. Hamid Azad, research associate
- Fardad Dadboud, PhD student
- Meng Lian, PhD student
- Daniel Charron, M.Sc. Student
- Mohammad Ahsan Akhlaque, M.Eng student

External members
- Dr. Varunkumar Mehta, NRC
- Dr. Iraj Mantegh, NRC
- Dr. Sreeraman Rajan, Carleton University

Funding agencies

- NRC
- NSERC

Thank You for Listening!