Université d'Ottawa | University of Ottawa

Miodrag Bolic

Professor Director of Computer Engineering Program School of Electrical Engineering and Computer Science (EECS) University of Ottawa mbolic@uottawa.ca

METHODS FOR UAV DETECTION

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Outline

• Introduction

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-
- d'Ottawa | University of Ottawa

| Time
| Time
|- Our group at UOttawa
|- Counter UAV systems
| Our work on Counter UAV d'Ottawa | University of Ottawa
 Hine
 Hine

- Our group at UOttawa

- Counter UAV systems

Nur work on Counter UAV

- Object detection versité d'Ottawa | University of Ottawa
|
| **Outline**
|- Our group at UOttawa
|- Counter UAV systems
|- Our work on Counter UAV
|- Object detection
|- Distance estimation d'Ottawa | University of Ottawa
 Hine

- Our group at UOttawa

- Counter UAV systems

Uur work on Counter UAV

- Object detection

- Distance estimation

- Payload detection – Distance estimation **Itline**
 Introduction

- Our group at UOttawa

- Counter UAV systems

Dur work on Counter UAV

- Object detection

- Distance estimation

- Payload detection

- Multitarget tracking

- Intent modeling
	-
	-
	-
	-
	-
- **Thine

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How the UNITY Systems

How the UNITY Systems

Accomplex tracking

Accomplex tracking

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 **Accomplision Control Material Control Multitarget tracking

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	-
- 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 **ntroduction**

- Our group at UOttawa

- Counter UAV systems

Vur work on Counter UAV

- Object detection

- Distance estimation

- Payload detection

- Multitarget tracking

- Intent modeling

esilient AI and future works **ntroduction**

- Our group at UOttawa

- Counter UAV systems

uur work on Counter UAV

- Object detection

- Distance estimation

- Payload detection

- Multitarget tracking

- Intent modeling

esilient AI and future works

Computational Analysis and Acceleration (CARG) Research Group

Motivation for Counter UAV systems Prsité d'Ottawa | University of Ottawa
 Motivation for Counter
 Technological Depression of UAVs

- Proliferation of UAVs

- Increasing use in civilian and

- Applications include delivery Vottawa | University of Ottawa
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 chnological Defe

Proliferation of UAVs . Natimetric of UAVs

- Increasing use in civilian and Terr

- Applications include delivery

- services, s **Motivation for Counter UA!**
 Technological

- Proliferation of UAVs

- Increasing use in civilian and

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- May

- Applications include delivery

- Prophetic Security

- Rapid evolution in

Technological

- - military sectors
- Vottawa | University of Ottawa
 Chinological Defermined Defermined and the University of OttaWare Proliferation of UAVs

 Increasing use in civilian and Termined Termined Proplications include delivery

 Applications i services, surveillance, and agriculture
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- **Chnological Deferminion In the Counter of Countrier**

Proliferation of UAVs

 Increasing use in civilian and Terr

military sectors

 Applications include delivery

services, surveillance, and

agriculture

iechnologica capabilities requires equally advanced countermeasures advanced countermeasures

Development of sophisticated Airspace Safety
- **Chnological**

Proliferation of UAVs

 Increasing use in civilian and

 Thermilitary sectors

 Applications include delivery

services, surveillance, and

agriculture

echnological Advancements

 Rapid evolution in UAV detection and response technologies

Defence and Security

- **er UAV systems**
Defence and Security
• National Defense and Counter-
Ferrorism
– UAVs pose a threat in asymmetric
marfare and terrorism **Terrorism UAV systems**
 fence and Security
 lational Defense and Counter-
 errorism

- UAVs pose a threat in asymmetric

warfare and terrorism

- Essential to detect and neutralize

hostile UAVs quickly **UAV systems**
 fence and Security

Intimal Defense and Counter-

Essential to detect and neutralize

— Essential to detect and neutralize

— Essential to detect and neutralize

— Potential threats to privacy and security **Example 18 Systems**
 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

• Securit **Defence and Security**

• National Defense and Counter-

• UAVs pose a threat in asymmetric

• Essential to detect and neutralize

• Essential to detect and neutralize

• Security and Privacy Concerns

• Potential threats
	- warfare and terrorism
	- hostile UAVs quickly
- - from unauthorized UAVs
- Potential threats to privacy and security **fence and Security**

lational Defense and Counter-

errorism

– UAVs pose a threat in asymmetric

warfare and terrorism

– Essential to detect and neutralize

hostile UAVs quickly

lecurity and Privacy Concerns

– Potenti activities, such as spying or smuggling **fence and Security**

Attional Defense and Counter-

errorism

- UAVs pose a threat in asymmetric

warfare and terrorism

- Essential to detect and neutralize

hostile UAVs quickly

lecurity and Privacy Concerns

- Potenti
- - interference with manned aircraft

4

Counter UAV systems and our focus

- Detection, identification, tracking and neutralization of unauthorized or hostile UAV systems
- **Counter UAV systems and our focus
• Detection, identification, tracking and neutralization of
• Detection includes processing sensor signals (camera, radar,
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R** RF, acoustic) from both ground and airborne sensors to detect a new object **Counter UAV systems and our focus
• Detection, identification, tracking and neutralization of
• unauthorized or hostile UAV systems
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• Detection, identification, tracking and neutralization of

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• Detection includes processing sensor signals (camera, radar,
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• Detection includes processing sensor signals (camera, radar,

RF, acoustic) from both ground and airborne sensors to detect

• Identification includes classi Detection, identification, tracking a
planauthorized or hostile UAV systems
betection includes processing sensor signals.
They acoustically from both ground and air
planarification includes classification of the
JAV
rackin Petection includes processing sensor signal
Petection includes processing sensor signal
The provident dentification includes classification of the
DAV
Tracking includes prediction of the UAV
There are also other topics not
- UAV
-
- UAV systems that we work on:
	-
	-

Counter UAV Detection: System Architecture

Operation of the system:

- **Operation of the system:**

1. Ground Radar and PTZ

camera serve as early

warning sensors to

detect the swarm.

2. The mission enerator camera serve as early warning sensors to detect the swarm.
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detected HA confirms the alert and initiates interceptor UAV flight towards the detected UAVs. **Operation of the system:**

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3. Interceptor UAV

per 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
- performs detection, tracking and payload classification.
- System runs AI models for sensor fusion and swarm characterization.
- swarm information are continually presented to the operator.

What are difficult problems for Counter UAV systems? Versité d'Ottawa | University of Ottawa
 **What are difficult probl

Counter UAV systems?**

• Detecting and classifying

• Detecting objects in front of

• Detecting objects in front of **What are difficult probler

Counter UAV systems?**

• Detecting and classifying

• Detecting objects in front of

• Detecting objects in front of

• Making sure that machine **What are difficult proble

Counter UAV systems?**

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• Making sure that machine

• Making sure that

- objects at large distances
- dark or unknown backgrounds
- learning models do not break when encountering unseen data/environments **Counter UAV systems?**

• Detecting and classifying

• Detecting objects at large distances

• Detecting objects in front of

dark or unknown backgrounds

• Making sure that machine

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when enco • Detecting and classifying

• 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 especi
- when fusing airborne and ground sensors
- 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.

Outline

-
- versité d'Ottawa I University of Ottawa

 Introduction

 Our work on Counter UAV

 Object detection • Our work on Counter UAV d'Ottawa | University of Ottawa

|
| Object detection
|- Object detection
|- Distance estimation
|- Payload detection – Distance estimation d'Ottawa | University of Ottawa
 | Line | Paylon Color Colo d'Ottawa | University of Ottawa

| Multimark | University of Ottawa

| Multimark | Object detection
|- Distance estimation
|- Payload detection
|- Multitarget tracking
|- Intent modeling
| esilient AI and future works **Thine**

Introduction
 Property Solution Counter UAV

- Object detection

- Distance estimation

- Payload detection

- Multitarget tracking

- Intent modeling

esilient AI and future works

- What is resilient AI
	-
	-
	-
	-
	-
- -
- **Outline**

 Introduction

 Our work on Counter UAV

 Object detection

 Distance estimation

 Payload detection

 Multitarget tracking

 Intent modeling

 Resilient AI and future works

 What is resilient AI

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The Object detection

- Distance estimation

- Payload detection

- Multitarget tracking

- Intent modeling

- Intent modeling

- What is resilient AI

- Directions in Counter UAV fi

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 d'Ottawa | University of Ottawa

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| A tain objective: classify the target drone into one of two

| alseses (loaded or unloaded) using the recorded

| ideos/images

| Sing experimental an Material Conversity of Ottawa

19 **Another Camer Conversity** the target drone into one of two

Ideos/images

Sing experimental and simulation dataset

- A quadrotor drone in both loaded and unloaded

cases as the target

oad detection using videos

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s (loaded or unloaded) using the recorded

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cases as the **bijective**: classify the target drone into one of two

s (loaded or unloaded) using the recorded

/images
 experimental and simulation dataset

quadrotor drone in both loaded and unloaded

ses as the target

nother qua
- Using experimental and simulation dataset
	- cases as the target
	- capture images of target drone
		-
		-
	- - approximately 100 meters from the camera
- Accuracy > 90%

Black arrow: forward-backward flying path Blue arrow: up-down flying path Red arrow: left-right flying path

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 $\frac{110}{2}$ pixels.
- Trained both with simulated and experimental data
- Future directions
- a
ure directions
• Including uncertainty in labels due to GPS
• expression the model errors in the model
	- Performing localization fusion after the association is done
	- Applying Kalman/particle filter to smooth $\frac{1}{30}$ the results

Multitarget tracking

- Sensor fusion
- Association between different sensors and targets to come up with unique IDs d'Ottawa | University of Ottawa
 Altitarget tracking

iensor fusion

ssociation between different

ensors and targets to come up

with unique IDs

Multi-view drone localization

- More than one observer drone

with a cam
- Multi-view drone localization
	- 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

Association: Proposed architecture

Architecture

- Synchronization and initialization: data preprocessing
- YOLO: bounding box information and ROI images extraction
- Position/Velocity model: LSTM tracker
- that the radar detection is more likely to belong to a bounding box
- Core fusion: Bottleneck residual block

Intent detection

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 Intent detection

 The types of intents considered include:

 reaching a specific destination or entering an area

of interest (AoI) d'Ottawa I University of Ottawa
 Lent detection

The types of intents considered include:

- reaching a specific destination or entering an area

- library of behaviours based on the application, of interest (AoI)
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	The types of intents considered include:

	The types of intenst considered include:

	The application or entering an area

	of interest (AoI)

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	types of intents considered include:

	aaching a specific destination or entering an area

	interest (AoI)

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	• kamikaze attack, smugglin acquisition
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Outline

-
- versité d'Ottawa I University of Ottawa

 Introduction

 Current work on Counter UAV

 Object detection versité d'Ottawa | University of Ottawa
|-
| Introduction
|- Current work on Counter UAV
|- Object detection
|- Distance estimation d'Ottawa | University of Ottawa
 ||tradeficient detection

- Object detection

- Distance estimation

- Payload detection

- Payload detection d'Ottawa I University of Ottawa
 Hine

Introduction

- Object detection

- Distance estimation

- Payload detection

- Multitarget tracking
	-
	-
	-
	-

– Payload detection – Multitarget tracking • Resilient AI and future works

-
- **It line**

Introduction

 Object detection

 Object detection

 Payload detection

 Payload detection

 Multitarget tracking
 Resilient AI and future works

 What is resilient AI

 Directions in Counter UAV field **The State of State State of State S**

Resilient and Robust AI

- **FRESILIENT AI ROBUST AI**
 RESILIENT AI ROBUST AI
 • Resilient AI refers to the ability of artificial intelligence systems to

maintain robust performance and functionality in the face of various

challenges, adversari maintain robust performance and functionality in the face of various challenges, adversarial conditions, or unexpected events. **FALL THEORY AT RESILIENT AND ROBUST AT**

• Resilient AI refers to the ability of artificial intelligence systems to

maintain robust performance and functionality in the face of various

challenges, adversarial conditions
- effectively even when confronted with disruptions or uncertainties.
- **FRESTITENT AND RODUST AT**

 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 unexpecte 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.

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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
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