

#### ASSURING AUTONOMY

# **Assurance of Remote Inspection Robots:** Some Rerspect AcDernard OBE FREng ProfJohn

### Overview

#### Agenda

- Challenges for remote inspection robots
- Assuring Autonomy International Programme
- An assurance perspective
  - System models
  - Assurance of ML
  - Safety processes
- A legal perspective
- Insights
- Conclusions

### **Remote Inspection**



# **Technical Challenges**

### **Remoteness and Other Issues**

- Autonomy
  - Able to make own decisions (but also shared control)
- Communication
  - Limited/no bandwidth and/or intermittent
  - Long round-trip delays and poor situational awareness
- Adaptive
  - Respond to changing environment and own state (repair)
- Long-lived
  - Missions of months or more

# **Challenges of Shared Control**

#### **Expectations on the Operator**

- What is it realistic to assume of drivers
  - How long can they retain situational awareness?
  - How will they react in an incident? For example some data from Volvo relating to emergency braking
    - 1/3<sup>rd</sup> took control promptly
    - 1/3<sup>rd</sup> took control late, waiting for the autonomy
    - 1/3<sup>rd</sup> took no action, wanting to avoid "interfering" with the autonomy

#### Automation Expectation Mismatch: Incorrect Prediction Despite Eyes on Threat and Hands on Wheel

Trent W. Victor, Emma Tivesten, Pär Gustavsson, Joel Johansson<sup>(D)</sup>, Fredrik Sangberg, and Mikael Ljung Aust, Volvo Cars, Gothenburg, Sweden

## **Assurance Challenges**

### Safety and Other Properties

- Generic assurance and regulatory challenge
  - A safe system cannot be deployed or is frequently unavailable (losing benefit)
  - An unsafe system is deployed (as it is approved due to lack of contrary evidence)
  - Similar issues for availability, mission effectiveness ...
- Addressing the technical challenges
  - Especially verification and validation for critical technologies including machine learning (ML)

# **Fundamental Challenges**

#### AI/ML vs Human Decision-Making

- Autonomous systems
  - Transfer decision-making from human to machine (AI/ML)
  - ML learns future behaviour generalising from training data
- Humans have a semantic model, e.g. know what a valve is and its likely behaviour
  - Machines do not have these models
- Humans have contextual models, e.g. know what a pipeline is
  - And the effects of pressure, corrosion, silting up ...
  - Machines do not have these models

## **Fundamental Challenges**

#### AI/ML Safety

#### Safety processes assume

- Know system boundary and it is fixed
- Know (can specify precisely) system behaviour
- Know system environment and can assess hazards
- Life-cycle progressively adds detail so can analyse easily
- With AI/ML
  - Behaviour not known precisely (learnt not specified)
  - Environment extremely complex (unpredictable)
  - Life-cycle highly iterative
  - Boundary and functions can also change

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### **Assuring Autonomy**

### **Response to Foresight Review**

- Review published in October 2016
  - Identified "white spaces" in assurance and regulation of RAS
- York-led programme
  - January 2018 to December 2022(3)
  - A strong focus on 'demonstrators' and working 'bottom up'
  - Developing international links, and seeking to influence policies and regulations



Foresight review of robotics and autonomous systems

Serving a safer world

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#### ML Assurance Survey

**ML** Verification

#### **Dynamic Safety cases**

# **Demonstrator Projects**

#### **Relevant to Remote Inspection**



### Safe Airframe Inspection using Multiple UAVs (SAFEMUV)

Improving the safety of autonomous unmanned aerial vehicle teams through the creation of a systematic robustness assessment process

#### Sense-Assess-Explain (SAX)

Building autonomous vehicles that can sense and fully understand their environment, assess their own capabilities, and provide causal explanations for their own decisions.





### Assuring Long-term Autonomy through Detection and Diagnosis of Irregularities in Normal operation (ALADDIN)

Increasing the safety of unmanned marine systems by helping the vehicles identify the cause of their adverse behaviour.

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### Assurance

#### Assurance and V&V

- Assurance can be thought of as:
  - Confidence that the system behaviour is as intended in the environment of use (as intended includes safe)
- For autonomy, three key elements to assurance
  - Defined intent know what it should do and avoid doing (e.g. safety) [Validation]
  - Correct implementation meets its intent [Verification]
  - Malfunction control behaves appropriately when things go wrong, e.g. sensors are affected by weather, internal components, etc. [Verification & Validation]

# A System Model

#### Sense-Understand-Decide-Act (SUDA)



- System operates cyclically
  - Understanding includes prediction, e.g. trajectory of drone
- AI/ML usually limited to Understand and Decide (SUDA)
- Variants of model, e.g. Sense and Understand merged

## **Assuring Machine Learning**

**ML Process and SUDA** 



## **Assuring Machine Learning**

Table 4. Open challenges for the assurance concerns associated with the Model Learning (ML) stage

Open Challenge	Desideratum (Section)
Selecting measures which represent operational context Multi-objective performance evaluation at run-time Using operational context to inform hyperparameter-tuning strategies Understanding the impact of hyperparameters on model performance	Performant (Section 5.4.1)
Decoupling the effects of perturbations in the input space Inferring contextual robustness from evaluation metrics	Robust (Section 5.4.2)
Identifying similarity in operational contexts Ensuring existing models are free from faults	Reusable (Section 5.4.3)
Global methods for interpretability in complex models Inferring global model properties from local cases	Interpretable (Section 5.4.4)
Inferring global model properties from local cases use [2]	
	Open Challenge Selecting measures which represent operational context Multi-objective performance evaluation at run-time Using operational context to inform hyperparameter-tuning strategies Understanding the impact of hyperparameters on model performance Decoupling the effects of perturbations in the input space Inferring contextual robustness from evaluation metrics Identifying similarity in operational contexts Ensuring existing models are free from faults Global methods for interpretability in complex models Inferring global model properties from local cases

#### Rob Ashmore, Radu Calinescu, Colin Paterson

- $\checkmark$  = activity that the method is typically used in;  $\checkmark$  = activity that may use the method
- $* \star$  = desideratum supported by the method;  $\approx$  = desideratum partly supported by the method

# **Assuring Machine Learning**

**AMLAS - Assurance of Machine Learning for RAS** 



- Defined assurance process for ML components
- Results in a {compelling?} safety case for ML component(s) of the system
- Considers safety of ML in system context

# **An Al Safety Process**

#### SUDA, AMLAS and More

- Safety processes
  - SOCA: acceptability
  - SACE: whole system
  - SAUS: understanding
  - SADA: decisionmaking
  - AMLAS: assurance of ML
- Shared control is addressed by SACE



SR – Safety Requirement

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# Legal Issues

### Mind the Gaps

- In many legal frameworks need to "fix where responsibility lies" to have a case
  - Autonomy can introduce "liability gaps" despite an accident can't attribute responsibility (appropriately)
  - For example, the Tempe autonomous vehicle fatality –
    Uber found to have no case to answer under Arizona law
    - Likely to be a widespread issue
  - Also, ethical perspective on when it is appropriate to attribute responsibility to (legal individuals)

Burton et al. "Mind the gaps: Assuring the safety of autonomous systems from an engineering, ethical, and legal perspective." Artificial Intelligence, Volume 279, February 2020

# **RIMA Project**

Robotics for Inspection & Maintenance

- EU Project funded by European Union's Horizon2020 initiative
  - Major focus is on infrastructure
- Report written by University of York covering legal framework for operating RAS in different countries recently published
  - Takes a legal and regulatory perspective
  - Some of the legal issues and constraints likely to be of wider significance

D7.4 Review of legal frameworks, standards and best practice in verification and assurance for infrastructure robotics



# Insights

#### From AAIP, RIMA, etc.

- Verification is hard
  - A lot missing, e.g. appropriate performance criteria, test coverage criteria informed by fault models for ML
- Validation is harder
  - Need to link to safety (availability, maintainability ...)
- Adaptation goes beyond (most) current regulations
  - Will need to consider dynamic risk assessment
- Shared control is problematic (NB ALKS)
  - Need refined safety processes with input from human factors specialists

# **Regulatory Strategies**

#### **Regulation and Innovation**

- No response is "mute" about AI and RAS
- Prevention-oriented proscribes use of aspects of AI and RAS, e.g. adaptation in operation
- **Control-oriented** seek to control the technology
- Toleration-oriented allow innovation, with a degree of scrutiny – i.e. largely responsive
- Adaptation-oriented changes to respond to the technology – but how do we keep pace?

## Conclusions

#### V&V for Inspection Robotics

- AAIP considering broad issues of RAS assurance
  - Focus on safety, but likely that approach to system models and ML assurance (AMLAS) of wider applicability
  - Some demonstrator projects of direct relevance
- Interested in collaborating on applications
  - Validate/refine AMLAS, encourage links for demonstrators
  - Address issues of "how much evidence is enough"
- Are open research challenges
  - For example, test coverage criteria, safe interaction of "swarms" of robots (and humans), and security-informed safety
  - Many will benefit from interdisciplinary approaches





### Funded by



