ANITI
ARTIFICIAL & NATURAL INTELLIGENCE
TOULOUSE INSTITUTE

ONERA
THE FRENCH AEROSPACE LAB

Certification of AI-based systems: challenges and promises

Certified
AI

Université Fédérale
Toulouse Midi-Pyrénées

Agenda

Introduction

- ANITI institute
- Aeronautical certification

System level analysis

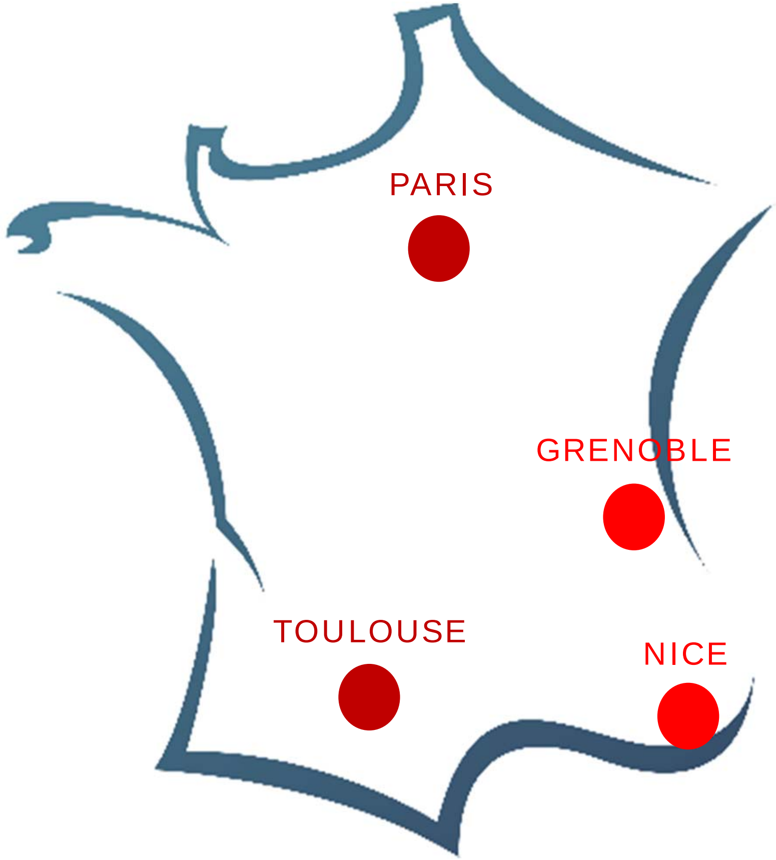
Zoom verification ACAS Xu

Zoom PHYDIAS

Conclusion

3iA: Interdisciplinary Institutes for AI

- Networked centers for research, education and economic development, with high international visibility
- 4 institutes
- Kick off: july 2019
- 4-year duration, renewable



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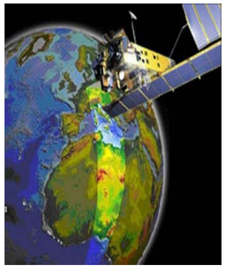
ANITI's Ambition

Make possible the sustainable use and development of AI in human critical applicative sectors (transport...) **and in** industry 4.0



Acceptability

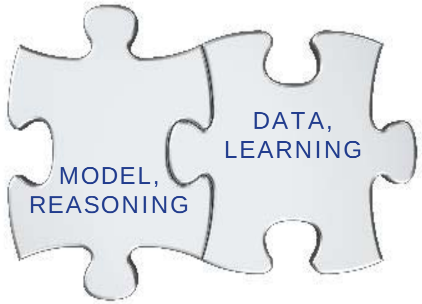
Fairness

Explainability

Robustness

Scalability

Adaptability



Hybrid **AI:** efficient combination of Model-based & Data-based AI

Partners

+50 PARTNERS

More to come !

Context: certification activities

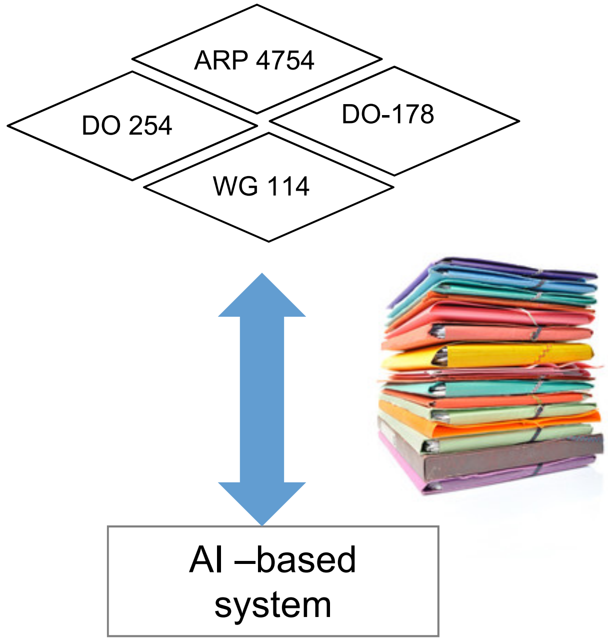
Certification:

- evaluation of an **argumentation**, to convince that a system (i.e., its architecture, its settings, including mitigation means. . .) satisfies **certification objectives** (expressed with AMC standards)

Difficulties :

- Existing standards are inapplicable [BCM+15]
  - o Data oriented specification

[BCM+15] Siddhartha Bhattacharyya, Darren Cofer, David J.Musliner, Joseph Mueller, and Eric Engstrom. Certification considerations for adaptive systems. Technical Report NASA, 2015



Certification: bibliography

- EASA – Concepts of Design Assurance for Neural Networks (CoDANN) – March 2020
- EUROCAE WG 114 / SAE G34 – Artificial Intelligence in Aeronautical Systems SoC (Statement of Concerns) – to be published soon
- AVSI (Aerospace Vehicule Systems Institute) – Machine Learning AFE 87 – June 2020
- White paper ANITI/DEEL/IRT Saint Exupéry: Machine Learning in Certified Systems – to be published soon

Talk: Focus on supervised learning and deep learning only

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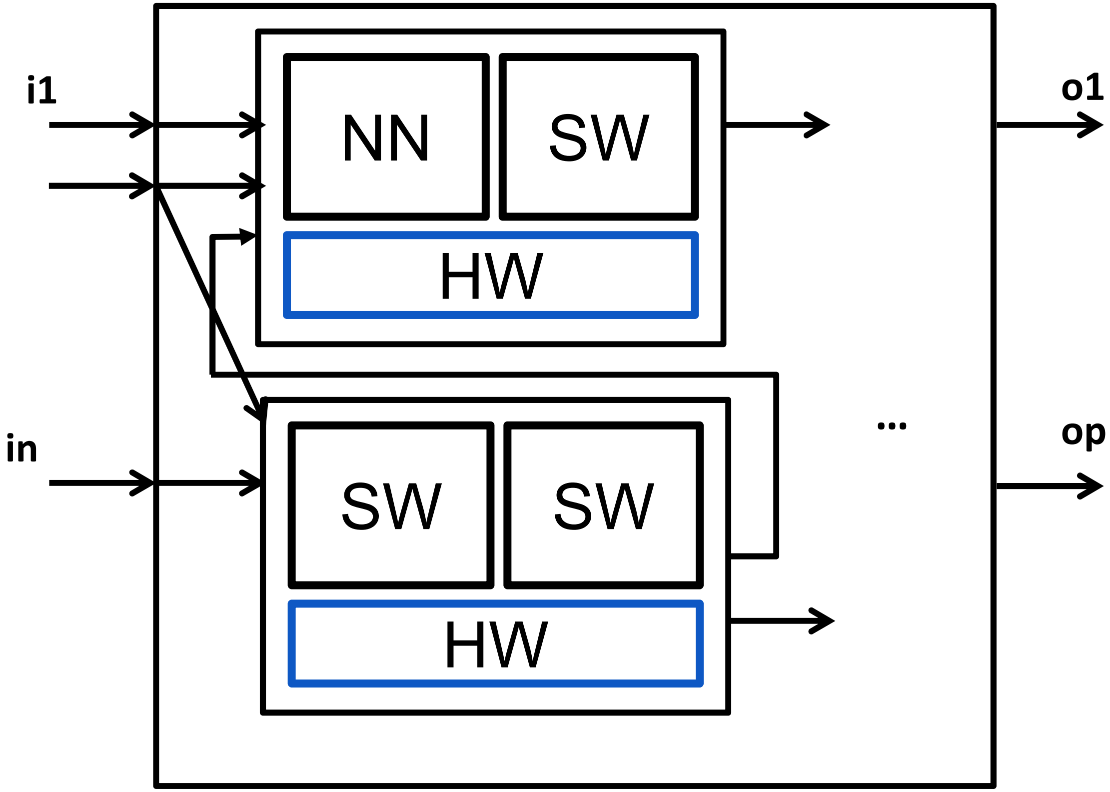
AI-based system



Objectives:

- ❑ System loss ≤ 10^{-9}FH
- ❑ Development process, test and verification at software level
- ❑ …

Example: ACAS Xu

GENERAL

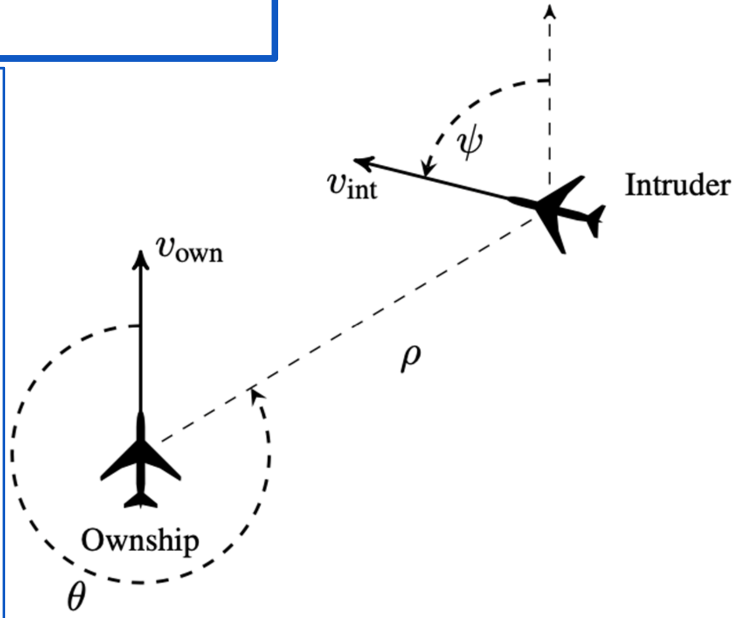
- Avoidance System for vertical and horizontal cooperative and non-cooperative avoidance
- Multi-Intruders

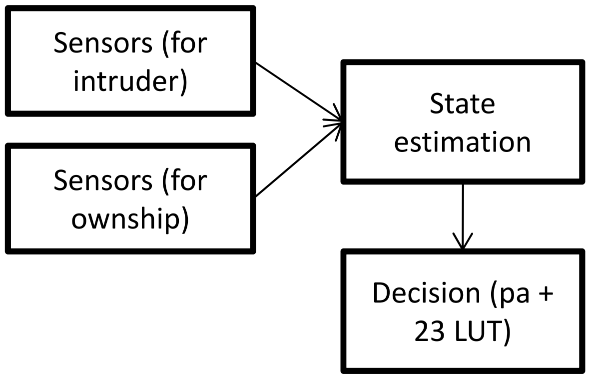
Why within AI consideration?

- On going studies to replace LUT (look-up table) with NN (seminal work Reluplex)

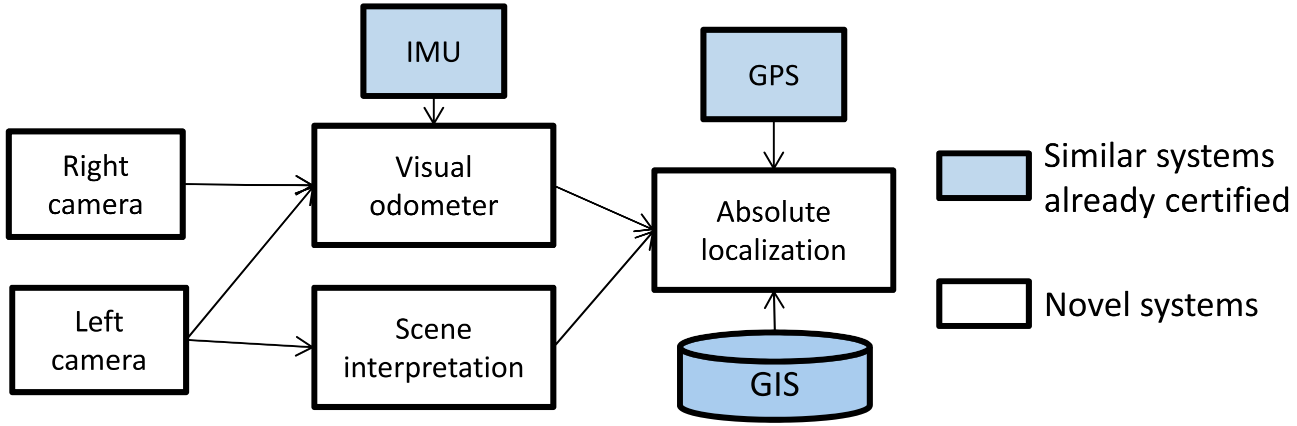
Safety Objective: FC = "the intruder enters the ownship enveloppe“ is Catastrophic

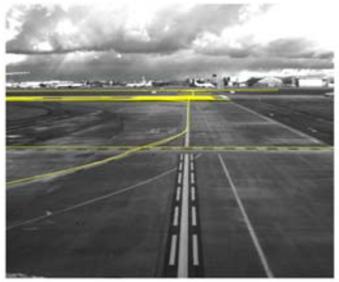
[Reluplex: An Efficient SMT Solver for Verifying Deep Neural Networks. Guy Katz, Clark Barrett, David L. Dill, Kyle Julian, Mykel J. Kochenderfer. CAV 2017]





Example: autonomous taxi driving





GENERAL

- Autonomous driving on pre-defined airports

Architecture:

- **Geographic information system (GIS)**: certified data base with airport maps
- **Visual Odometer (VO)**: estimate the trajectory wrt some relative reference
- **Scene Interpretation (SI)**: build a description of the scene
- **Absolute localization (AL)**: estimate the absolute position by fusing information

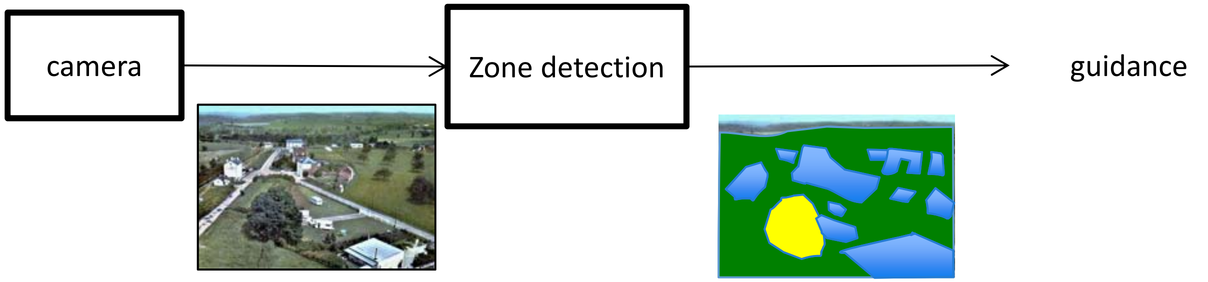
Safety Objective: FC = "the function provides a wrong position without the error being detected“ is Hazardous

Example: UAS emergency landing

GENERAL:

- Autonomous flight on a pre-defined trajectory
- Several back-ups in case of internal failures. Among the back-ups, emergency landing based on vision

Architecture: Mixing scene interpretation algorithms

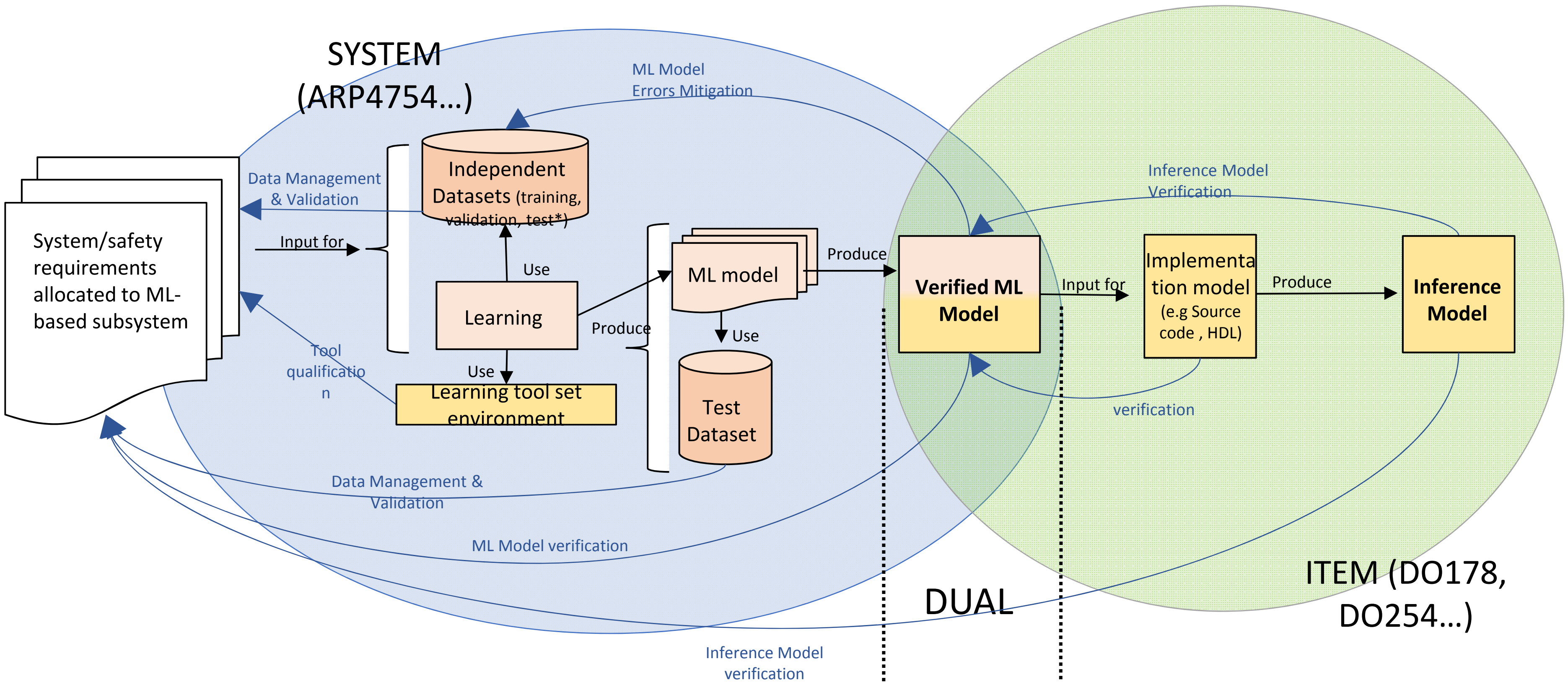


RGB image of the in front ground

Zones identification

Safety Objective: FC = ”deciding to land on a non planar zone, or a zone where a person or a property (car, house, warehouse) stand ” is Hazardous

EUROCAE WG114 current vision



Main examples of use for NN

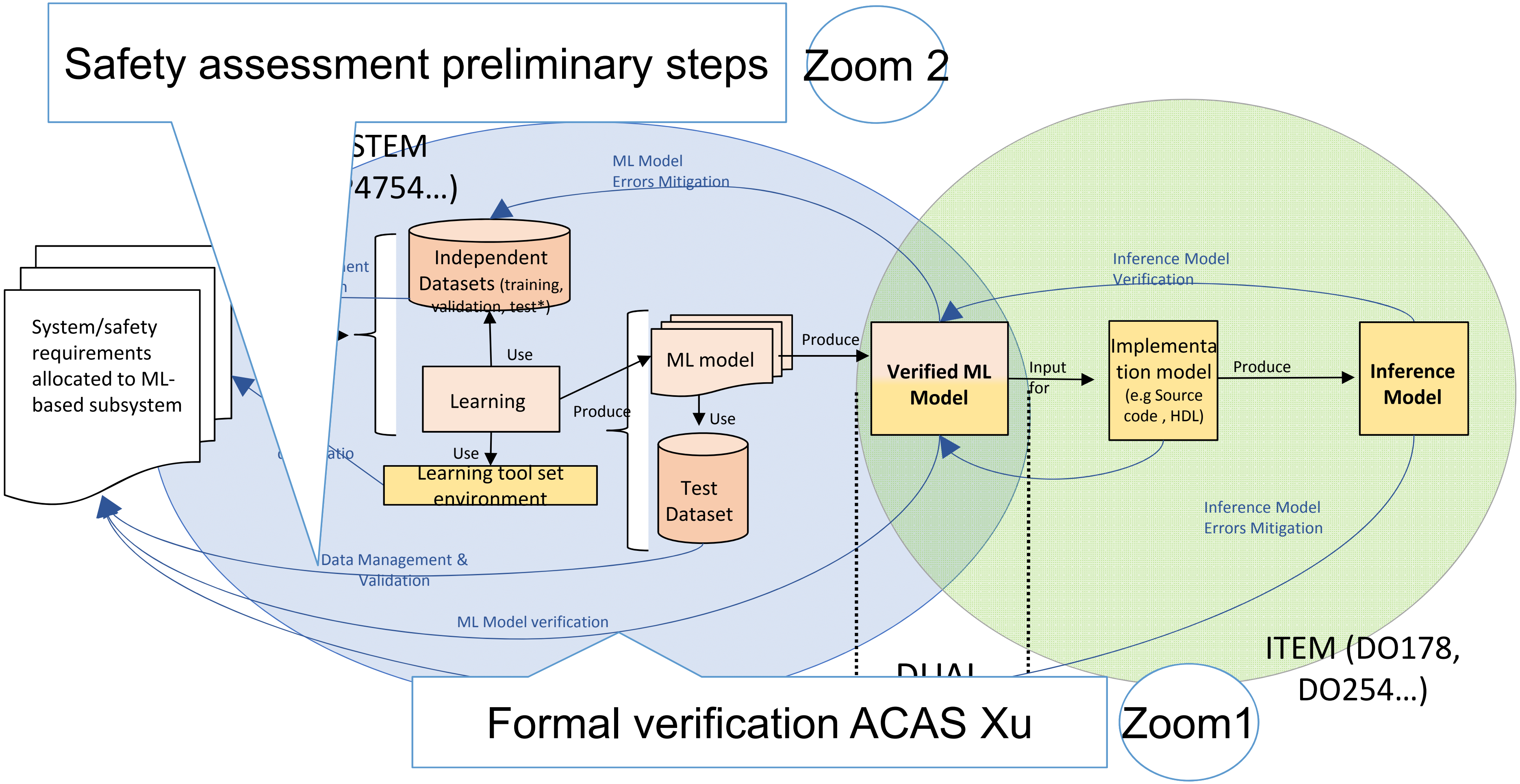
- **Existing certified SW**
  - Ex: certified look up tables replaced by NN
  - Why: increase performance of code (smaller memory footprint)

- **Embedding of design computation code (surrogate model)**
  - E.g.: certified Fortran code that takes 5hours to compute a result
  - Why: increase performance of the aircraft

- **Embedding of fully new system**
  - Ex: obstacle detection with camera
  - Why: increase of autonomy, …

Difficulty / novelty in terms of certification

Technical zooms



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Introduction

System level analysis

Zoom verification ACAS Xu

- Collaborative work with DEEL partners (Mathieu Damour – Scalian Florence De Grancey – Thales, Christophe Gabreau – Airbus, Adrien Gauffriau – Airbus, Jean-Brice Ginestet – DGA, Alexandre Hervieu – DGA, Ludovic Ponsolle – APSYS)
- Verification tool Arthur Clavière PhD Collins Aerospace (co-supervised with Eric Asselin – Collins Aerospace, Christophe Garion – ISAE Supaéro)

Zoom PHYDIAS

Conclusion

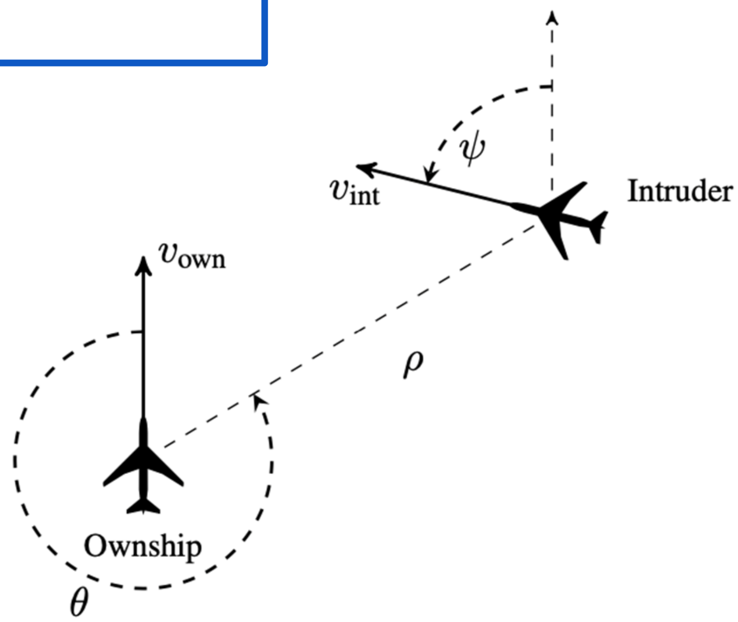
ACAS Xu overview

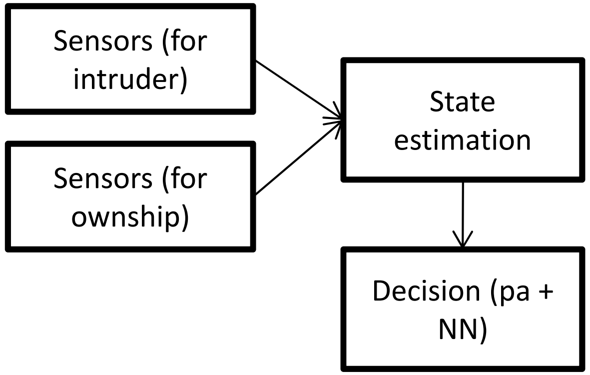
GENERAL

- Avoidance System for vertical and horizontal cooperative and non-cooperative avoidance
- Multi-Intruders
- EUROCAE WG 75.1 / RTCA SC 147

HOW IS IT WORKING

- Model of vehicle with Markov Decision Process
- Dynamic programming to compute Offline cost tables that enable to never have a vehicle in the collision volume
- Validation: large number of simulation and some flight tests



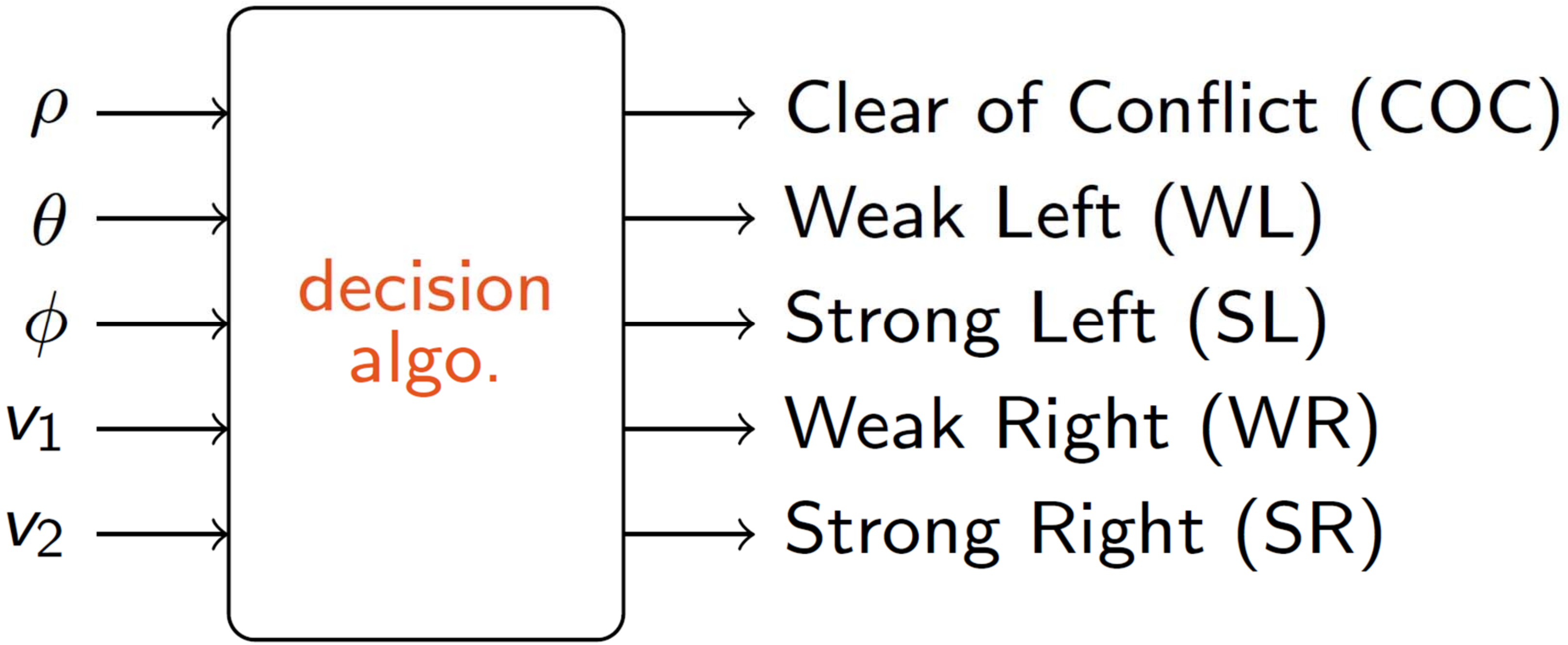


Why neural networks?

Several American universities (Standford, MIT) try to replace the LUT with NN

➔Gain in memory footprint (from 4Go to 3Mb)

➔Good anti collision performance



Certification proposed approach

How to adapt the certification activities of the ACAS Xu

- when replacing the LUT (lookup tables) with NN

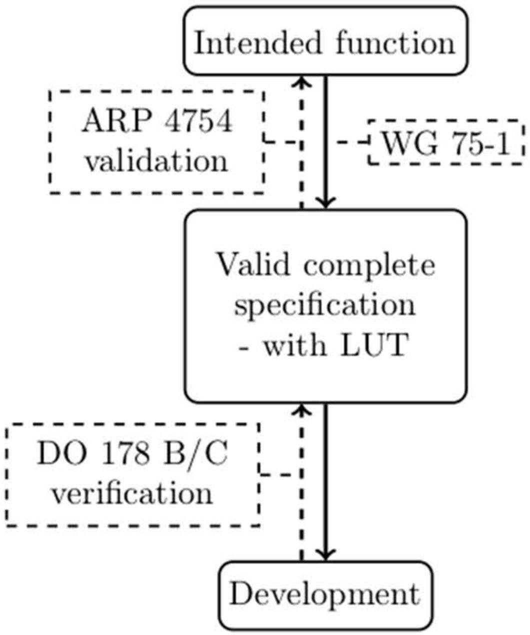


Figure 3: Classic approach

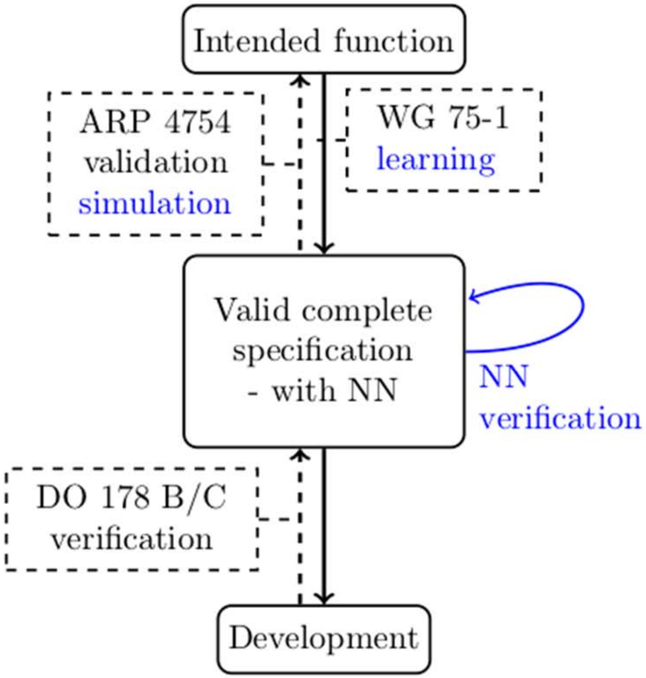
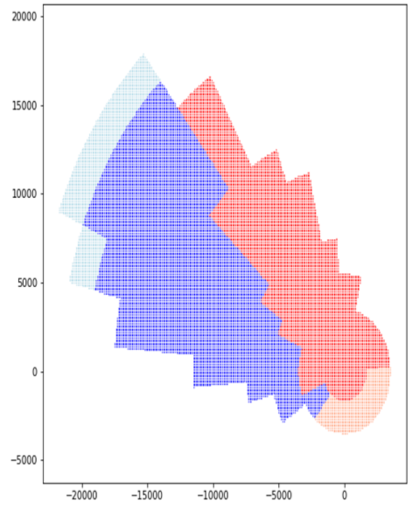
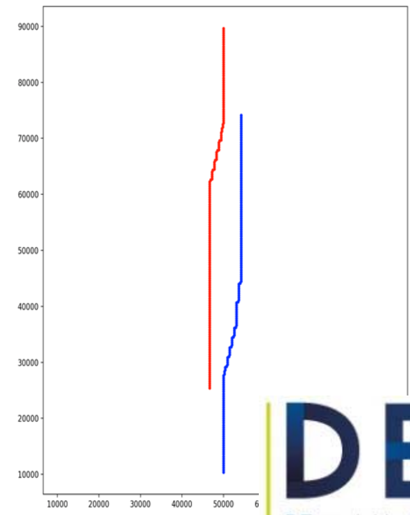


Figure 4: New approach

Developed supporting tools for ACAS-Xu

- **Get Binary tables provided by RTCA**
- **Parsing using documentation and guessing**
- **Enable**
  - Python Notebook to explore configuration
  - ACAS-Xu Simulator





Learning

- **Number:**
  - A la Reluplex: 45 NN (depend on the previous action and vertical)
  - A la Marabou: 1NN
  - 1 per (decision, pa): diverse shape of « function »
- **Structure:**
  - A la Reluplex: 6 layers and 300 neurons per layer
  - Design space exploration to find « optimal » structure
- **Training set:**
  - all LUT in learning data set: to be as close as possible to the LUT
  - Splitting strategies
  - Data augmentation

Verification

- **NN approximate the LUT => not the same exact behaviour**
- **How to formally define an "acceptable behaviour"**
- **Currently: no answer**

- **Literature: 10 properties defined in the Reluplex paper**
  - example property 3: "*If the intruder is directly ahead and is moving towards the ownship, the score for COC will not be minimal.*"
  - Shall hold for all of the 45 NNs except three of them

Input constraints (5D box):

$$(1500 \text{ ft} < \rho < 1800\ ft) \wedge (-0{,}06\ rad < \theta < 0.06\ rad) \wedge (3.10\ rad < \phi < 3.14\ rad) \wedge (980\ ft.s^{-1} < v_1 < 1200\ ft.s^{-1}) \wedge (960\ ft.s^{-1} < v_2 < 1200\ ft.s^{-1})$$

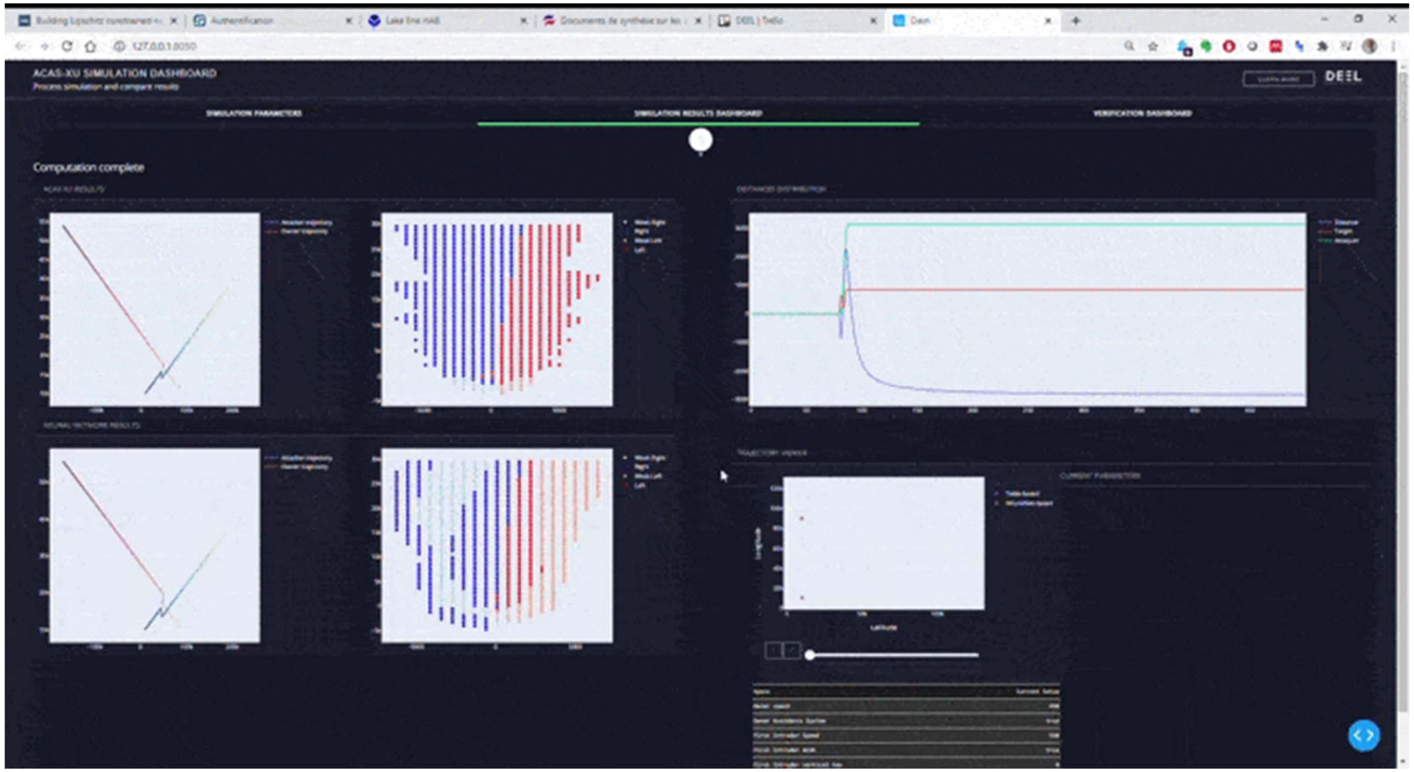
Output constraints (5D Halfspace polytope):

$$(COC > WL) \vee (COC > WR) \vee (COC > SL) \vee (COC > SR)$$

➔ Insufficient from certification perspective. Combination with simulation

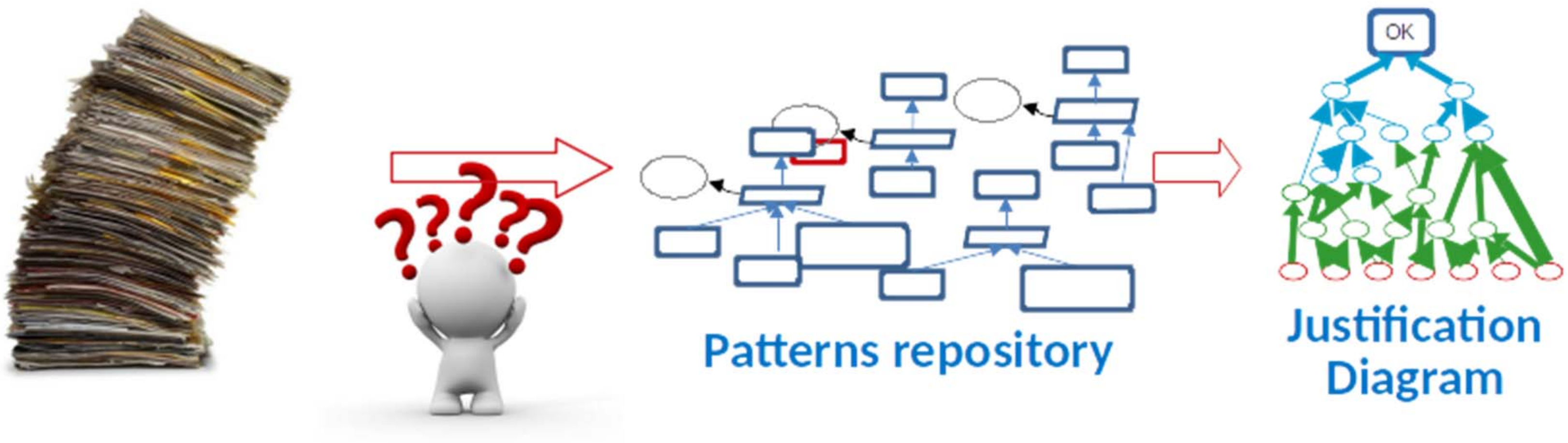
Simulation

- Intensive simulation
- Analysis of several indicators (partial explanation, …)



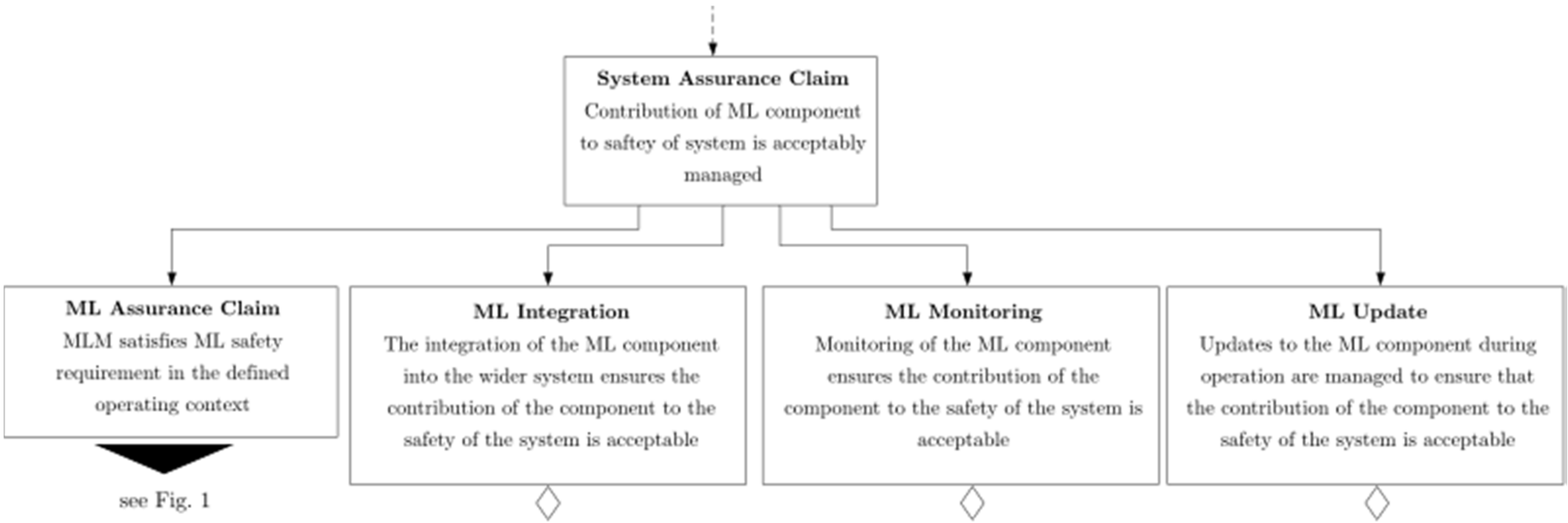
Assurance case reminder

- **structure, organize and share all these V&V items between stakeholders**
- ***an organized argument that a system is acceptable for its intended use with respect to specified concerns (such as safety, security, correctness)***
- **Concretely**
  - list necessary evidence related to the certification
  - structure key evidence (rationale)



Assurance case for ML

Assurance Argument Patterns and Processes for Machine Learning in Safety-Related Systems. Chiara Picardi, Colin Paterson, Richard Hawkins, Radu Calinescu, Ibrahim Habli. Proceedings of the Workshop on Artificial Intelligence Safety (SafeAI 2020) 2020



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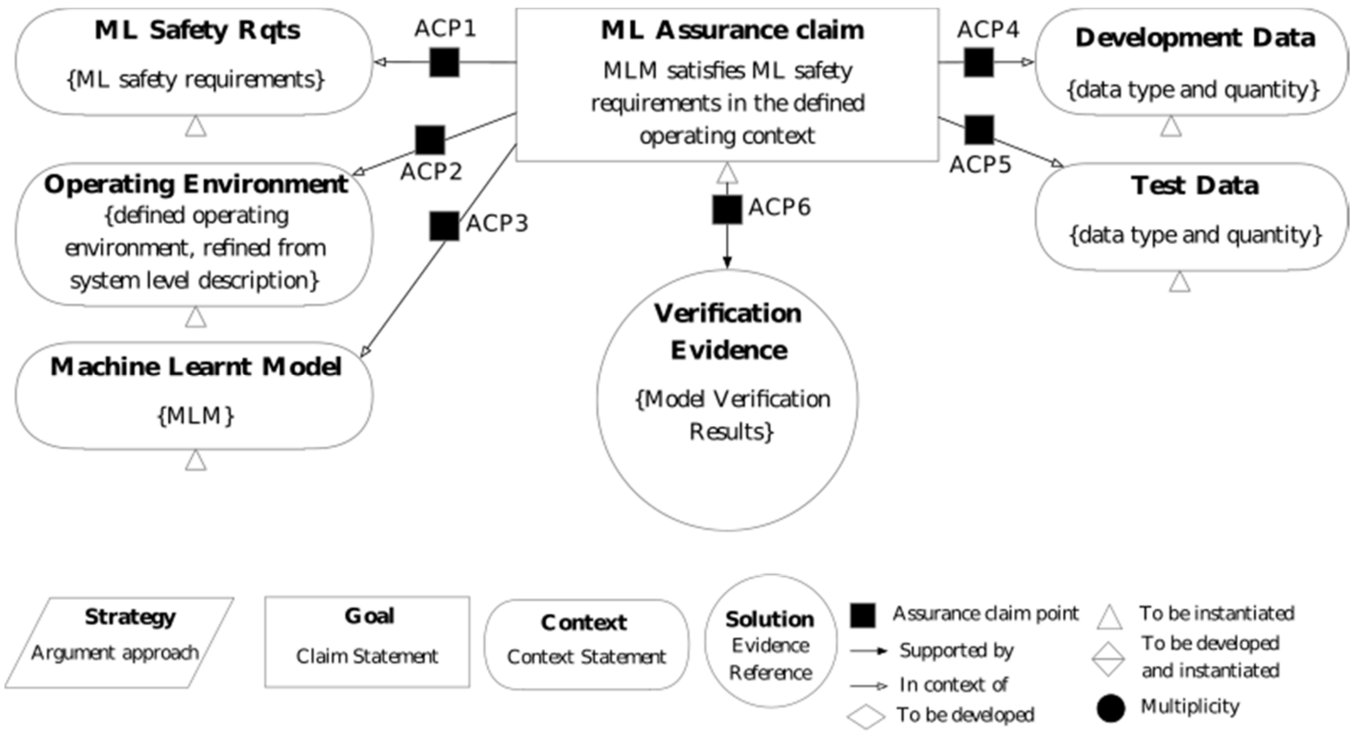
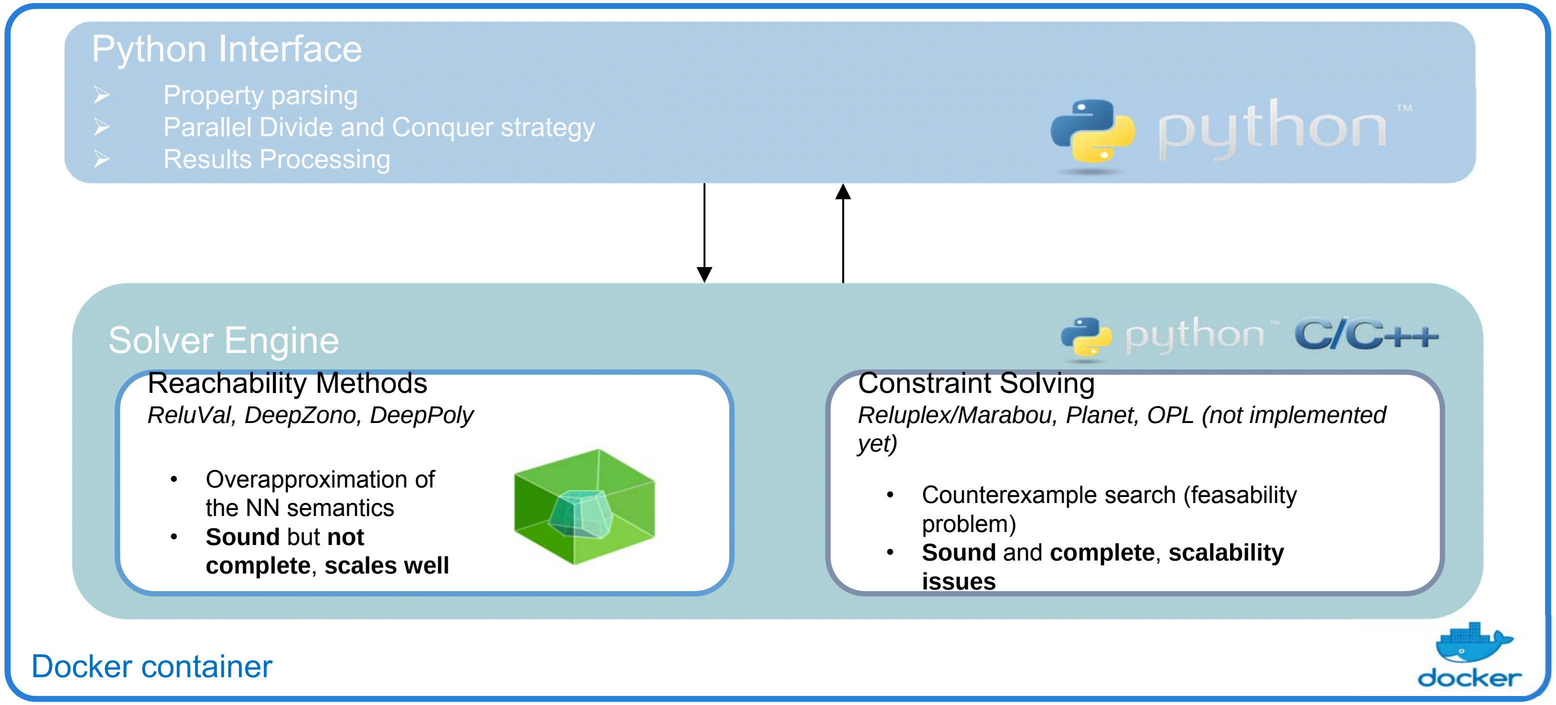


A Unified Framework for NN Verification

- **Common julia verification tool developed by C. Liu, T. Arnon, C. Lazarus, C. Barrett, and M. Kochenderfer, "Algorithms for Verifying Neural Networks," 2020 ➔ re-coded from scratch**
- **Proposed approach: Interface to call directly the original tools**



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Introduction

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Zoom PHYDIAS

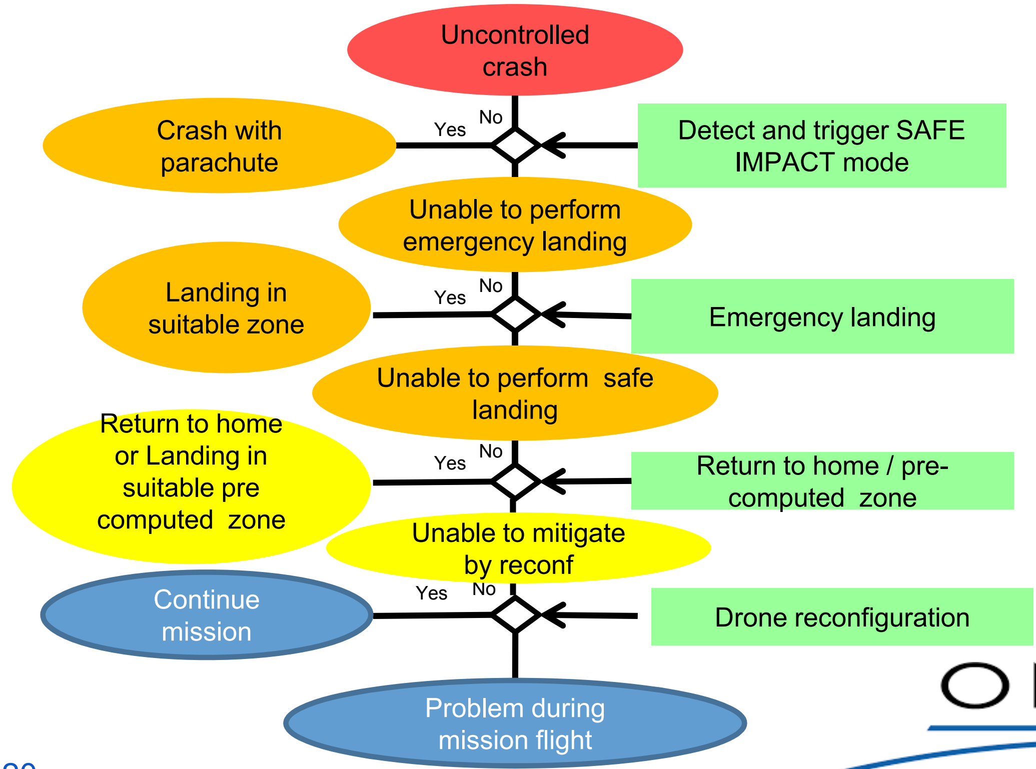
- Collaborative work with Frédéric Boniol, Adrien Chan-Hon-Tong, Kevin Delmas, Alexandre Eudes, Stéphane Herbin, Guy Le Besnerais, Martial Sanfourche

  [Challenges in certification of computer vision based systems for civil aeronautics. Aerospace Lab 2020]

Conclusion

Ground risk management

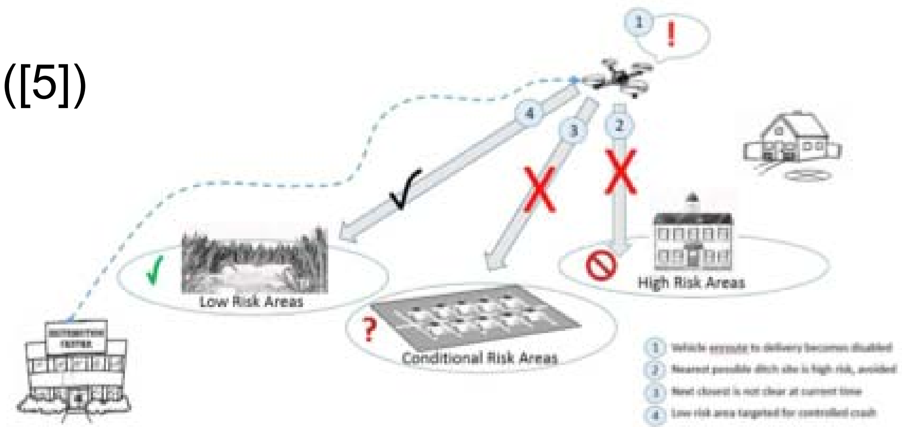
- Nominal flight plan: above sparsely populated zones
- Monitoring of flight plan correct following and health status of the drone
- In case of hazard, pre-defined procedures



State of the art

Numerous work on the topic "Autonomous crash management to a safe and clear site"

- "SafeUAV : Learning to estimate depth and safe landing areas for UAVs from synthetic data". Marcu et al. ECCV 2018. ([1])
- "UAV Emergency Landing Site Selection System using Machine Vision". Faheem et al. Journal of Machine Intelligence. 2015. ([2])
- …
- Safe2Ditch : start-up Nasa ([5])

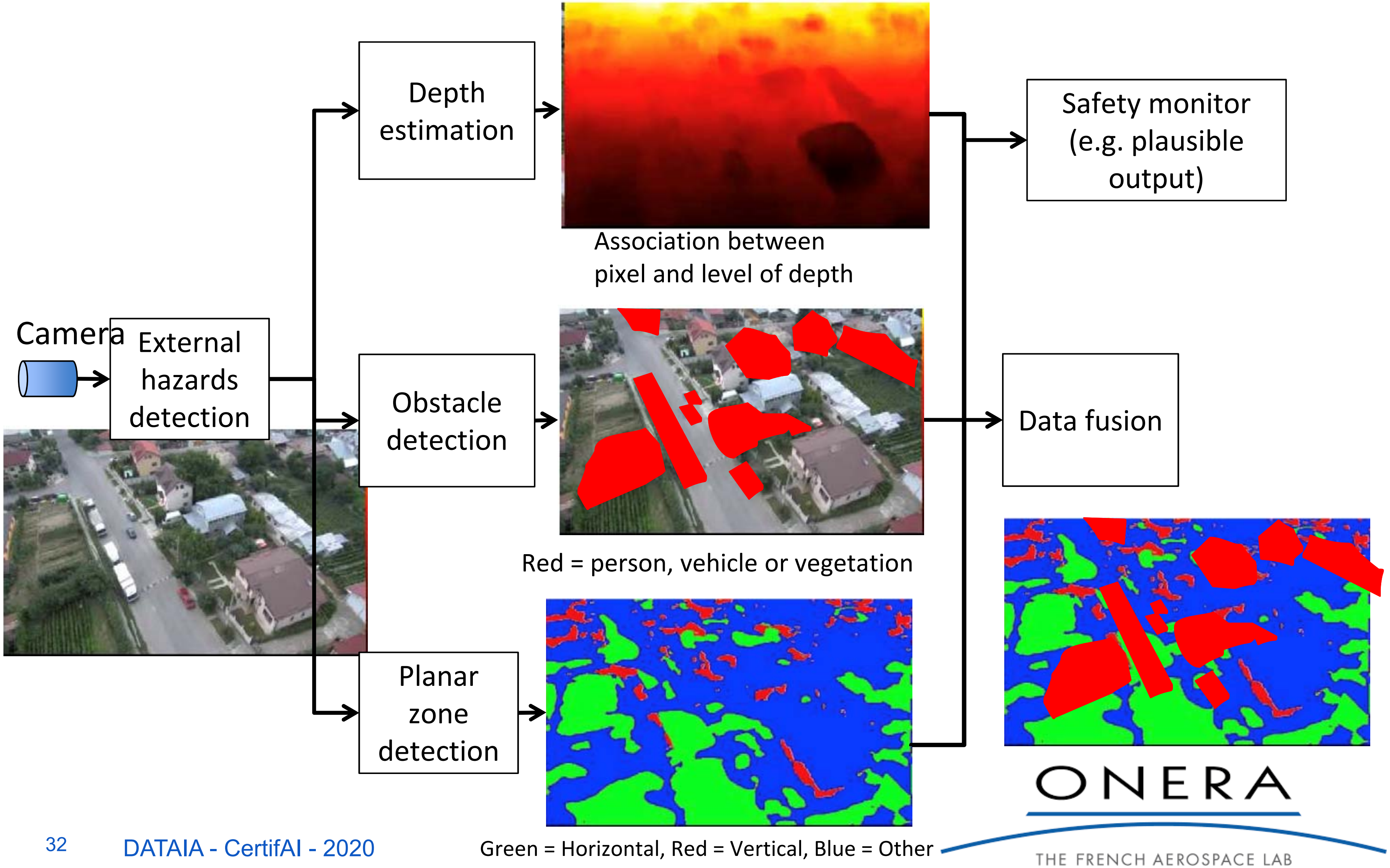


Sample Safe2Ditch Operational Scenario. Image credit: NASA

Safety considerations

- **Case 1 : not considered in the safety argumentation (safe drone)**
  - Emergency landing is an additional barrier, « best effort » (cf literature)
- **Case 2 : unconsidered in the safety argumentation (our case)**
  - FC = ”deciding to land on a non planar zone, or a zone where a person or a property (car, house, warehouse) stand ” is Hazardous
  - What is the detailed architecture?
  - What are the hazards?
  - How to realize the safety assessment?

Detailed architecture – 3 independent chains



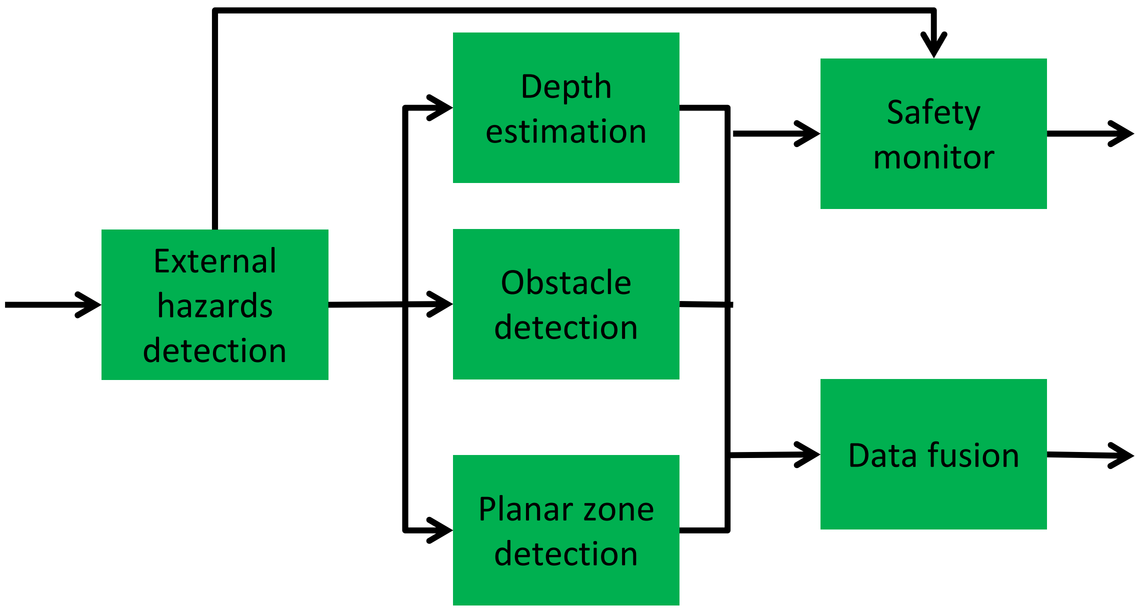
Identification of hazards

- **External events / hazards**
  - Vision hazards [ZMH+17] – CV HAZOP: Illumination (low illumination → low contrast); propagation conditions (e.g. smoke, haze); camera settings (e.g. aperture)…
  - occlusion
  - unreliable contrasted edges between illuminated areas and shadows
  - reflections related to water surface
  - …
- **Algorithm associated hazards** :
  - Incomplete specification: existing data sets for planar ground detection are very small
  - bad generalization
  - lack of robustness
  - …

[ZMH+17] Oliver Zendel, Markus Murschitz, Martin Humenberger, and Wolfgang Herzner. How good is my test data? introducing safety analysis for computer vision. International Journal of Computer Vision, 125(1-3):95–109, 2017.

Safety assessment

- How to associate some failure rate to a failure event that is not a hardware failure?
- How to define the failure propagation?
- How to combine probabilistic behaviour to determine the overall safety?



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Conclusion & future work

- **Lot’s of pending work**

- **Finalisation of the ACAS Xu assurance case and associated evidence activities**

- **Safety assessment experiments for the emergency landing**

- **Implementation considerations for neural network**