LARD 2.0: Enhanced Datasets and Benchmarking for Autonomous Landing Systems

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More and more initiatives to integrate ML algorithms

Example: Airbus project (2018 – 2020) ONERA contributor

ATTOL (Autonomous Taxiing, Take-Off and Landing)

Copyright Airbus https://www.youtube.com/watch?v=9TIBeso4abU

Example: Boeing Beacon EASA-IPC project (2025). Taxi obstacle detection

Copyright Boeing https://www.youtube.com/watch?v=lAxtPvQVt3c

Outline

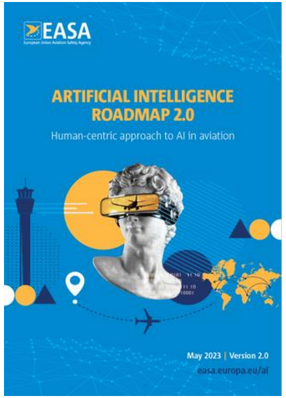
- **Introduction: starting from LARD**
- LARD V2
- Conclusion

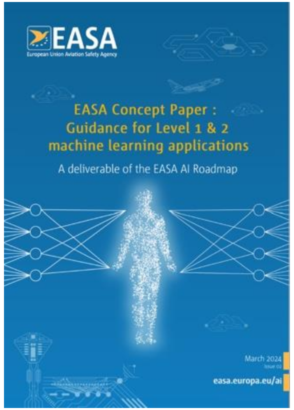
Beginning of LARD

ANITI Université Fédérale Toulouse Midi-Pyrénées

DEEL DEpendable & Explainable Learning

- ANITI / DEEL project (2019 – 2023):
  - Certification mission addresses the certification of systems embedding machine learning (ML) algorithms.
  - Selection of use cases for experimenting certification activities / process (in line with EASA guidance and SAE G34 / EUROCAE WG 114)
- First use case was ACAS-Xu (will appear as a use case of ED 324)
- **2022: we wanted a more challenging use case**





EUROCAE

SAE INTERNATIONAL

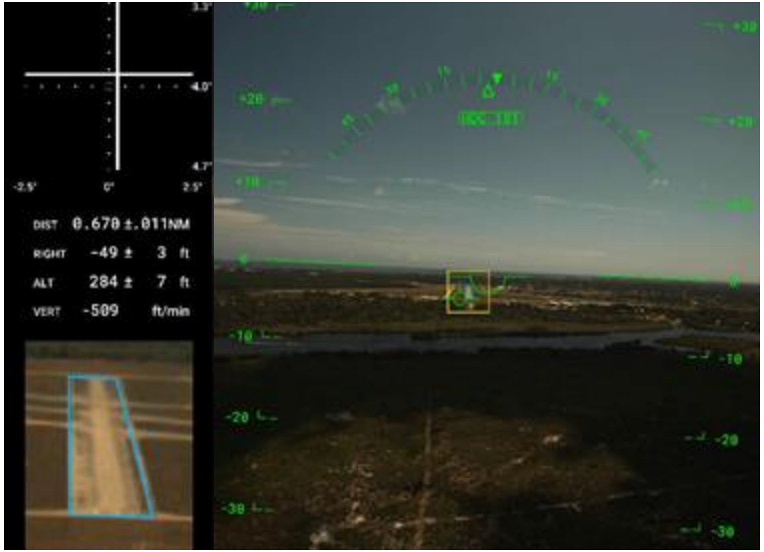
New ED-324/ARP6983 (Machine Learning)

2022: growing interest on VBL

Development view of Daedalean's VLS: *Neural Network Based Runway Landing Guidance for General Aviation AutoLand*

"[…] a detailed walk-through on the design and evaluation of a machine learning-based system targeted to safety-critical applications. We showed how the W-shaped process provides elements for a thorough safety assessment and performance guarantees of an ML system. We demonstrated how this is done by exploring data requirements, generalization of neural networks, out-of-distribution detection […]"

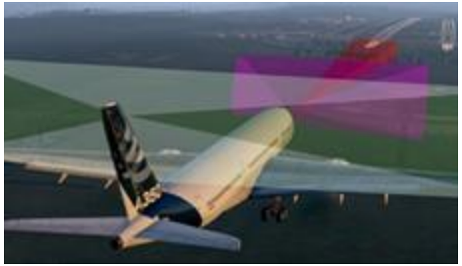
- Dr. Corentin Perret-Gentil, head of Daedalean's ML-research group.



Motivation – visual-based landing (VBL)

- Human eye primary landing sensor
  - Pilots’ landing trainings without instruments
  - Federal Aviation Laws impose minimal visibility:
    - 14 CFR §91.155: operating under **VFR = 3NM of visibility** [...]
    - 14 CFR §121.649: landing under **VFR = 1NM of visibility** [...]
- Usefulness ?
  - **Reducing** pilots' **cognitive loads**: majority of landing accident due to human errors
  - **Autonomous landing**: single pilot operation (SPO) + incapacitation

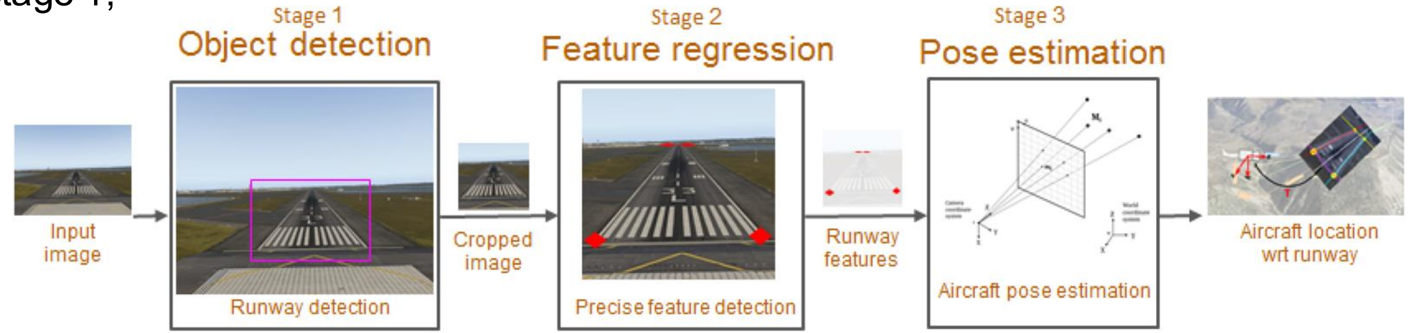
Vision Based AI algorithms appealing for guidance and navigation during the landing stage



LARD: Single runway detection during landing approach

Intended function 1 (VBL intended function): The *intended function* is the pose estimation of the aircraft with respect to the airport runway when the aircraft flies within the generic landing approach cone. The pose is estimated from several sensors, including a camera positioned at the aircraft's nose and directly facing the runway during the landing.

- Focus on stage 1,



Video https://www.dailymotion.com/video/x8l689i

- **2022: No available (open source) data set**

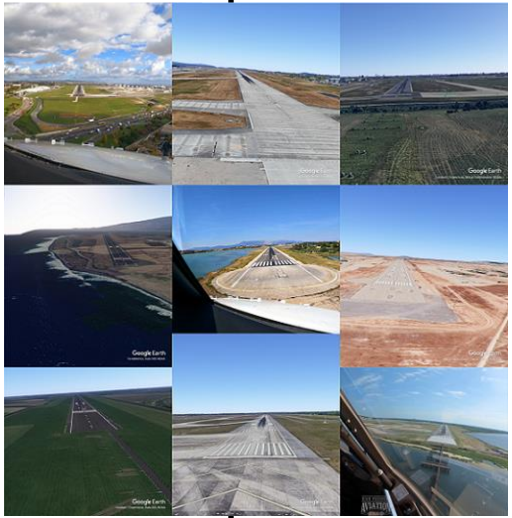
LARD – Landing Approach Runway Detectic

LANDING APPROACH RUNWAY DETECTION

- Task: Detection of runways during landing
- On a single frame (no video)
- Camera
  - under the aircraft nose
  - faces the runway

Data collection strategy

- Synthetic data from Google Earth Studio,
- real footage image



LARD -- Landing Approach Runway Detection--Dataset for Vision Based Landing . Ducoffe et al. 2023. ArXiv https://github.com/deel-ai/LARD

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- Introduction: starting from LARD
- **LARD V2**
  - **ODD**
  - Data diversity
  - Data set
  - ML benchmarking
- Conclusion

LARD V2

- ANITI 2 / DEEL 2 project (2025 – 2029)

- **Objectives:**
  1. Improve ODD (Operational Design Domain)
  2. Enhancing Dataset Diversity (Microsoft Flight Simulator, X-Plane, Arcgis…)
  3. Benchmark ML models for runway detection

ODD – Operational Design Domain

Seminal definition (from SAE J3016 standard):

"The operating conditions under which a given driving automation system or feature thereof is specifically designed to function, including, but not limited to, environmental, geographical, and time-of-day restrictions, and/or the requisite presence or absence of certain traffic or roadway characteristics"

EASA definition (Concept Paper Issue 2)

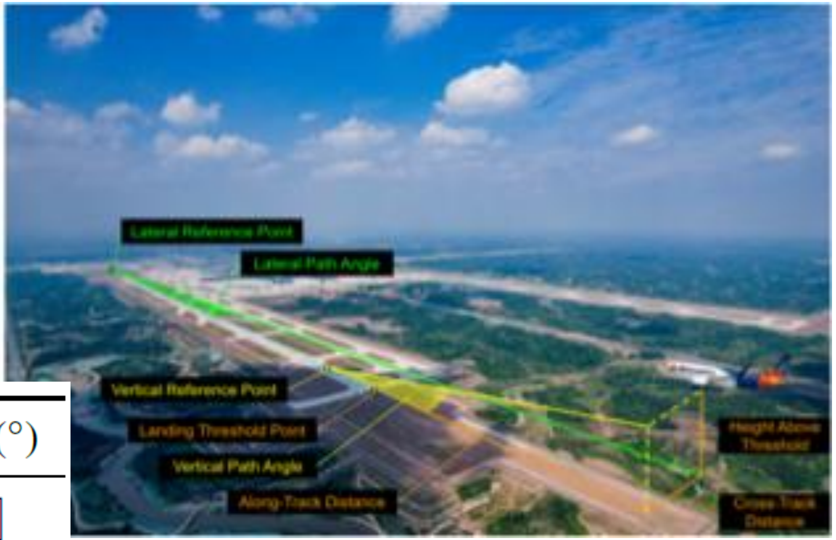
"The operating conditions under which a given AI/ML constituent is specifically designed to function as intended, including but not limited to environmental, geographical, and/or time-of-day restrictions «

System-level ODD – Approach cone

Definition of a generic landing approach cone

ODD 1 (of VBL): *The VBL system must permit the landing as long as the aircraft is in the generic landing approach cone.*

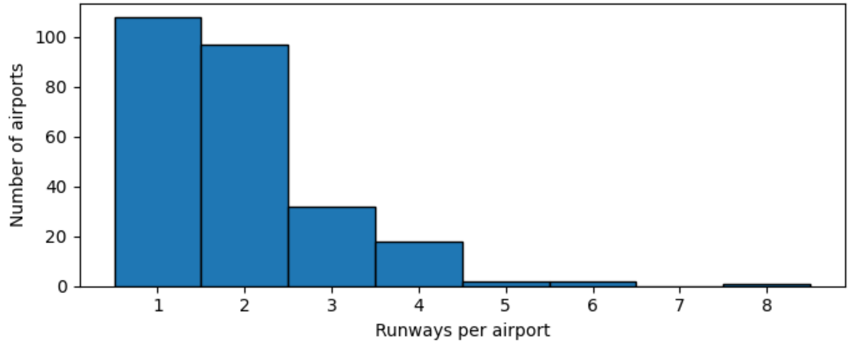
- lateral path angle: [-3° ,3°]
- Vertical path angle: [-1.8° ,-5.2°]
- Pitch: [-5° , 15°]



Along-track distance (m)	Yaw range (°)	Roll range (°)
$[-6000,\ -4500]$	$[-24,\ 24]$	$[-30,\ 30]$
$[-4500,\ -2500]$	$[-24,\ 24]$	$[-15,\ 15]$
$[-2500,\ -280]$	$[-18.5,\ 18.5]$	$[-10,\ 10]$

Other hypotheses

- multiple-runways airports (while single-runway for LARD V1)
- 260 single- and multi-runway airports
  - Methodology: Identification of 300 airports with the most traffic world-wide, then reduced this list according to the quality of the run-way imagery (e.g. badly pixelated images)
- presence of piano
- optimal weather conditions



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Synthetic data generators

Google Earth Studio (LARD V1)

Microsoft Flight Simulator

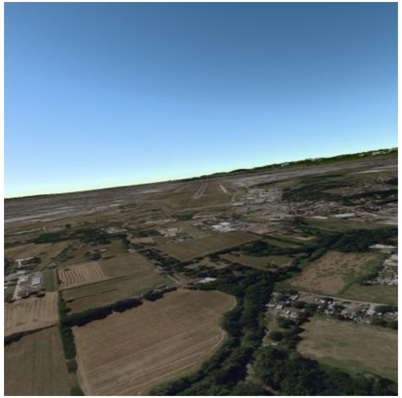
Xplane

ArcGIS

Toulouse – runway 14R

Coordinate: 43° 39’44. 4"N 1° 19'31.0"E

Altitude 245 m



BingMap

Interoperability

Use of Cesium for Google Earth, ArcGIS and Bing Maps

Common .yaml format:

- A header of global information (with image size and field of view)
- A series of poses (with position, attitude, the targeted airport / runway)

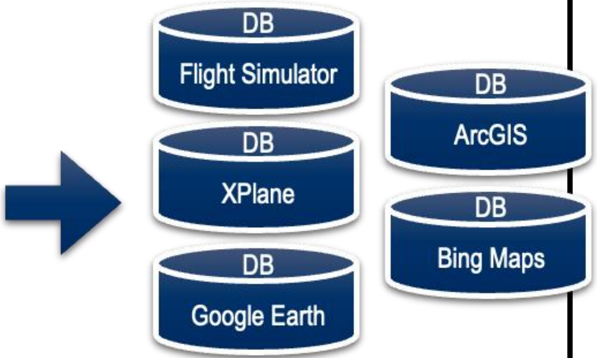
Example: Toulouse – runway 14R, Coordinate: 43° 39’44. 4"N 1° 19'31.0"E , Altitude 245 m


```yaml
airports_runways:
  LFBO:
  - 32R
  - 14L
  - 32L
  - 14R
image:
  height: 1024
  width: 1024
  fov_x: 60.0
  fov_y: 60.0
  watermark_height: 0
```

```yaml
poses:
- uuid: 468b7855-064c-473d-b0bd-b7bee9b26bab
  airport: LFBO
  runway: 14R
  pose:
  - 1.3271272157529728
  - 43.66035506372285
  - 286.17865699835124
  - 140.47160354531033
  - 86.10303716551084
  - 6.766881036328359
  time:
    second: 1
    minute: 0
    hour: 10
    day: 1
    month: 6
    year: 2020
runways_database: ./data/runways_db_V2_GES.json
trajectory:
  sample_number: 1
```

Interoperability issue

- Airports open database https://ourairports.com
  - corners of the runways of all airports in the world.
  - highly valuable but not 100% accurate
    - Position error around a few meters or more
- Inconsistency on the coordinates between sources
  - Spatial offset
- Workaround
  - Dedicated database for each source
  - How to construct them: **Calibration procedure**



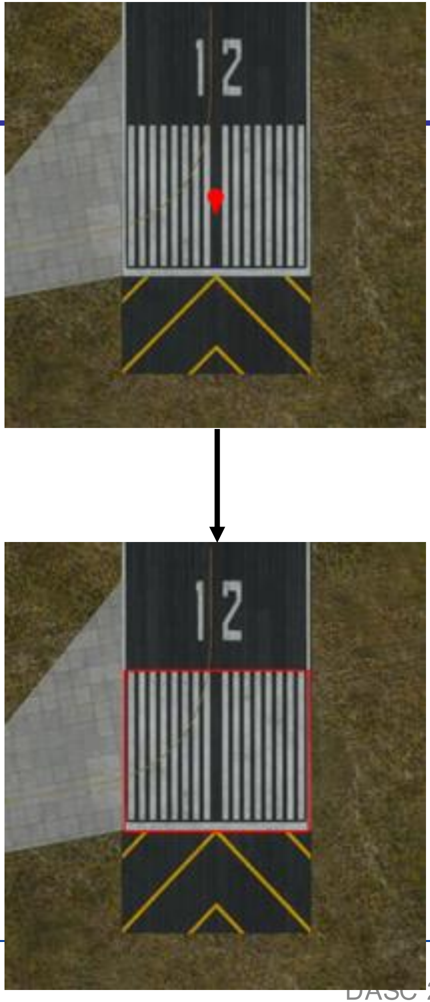
Calibration procedure – step 1

- Step 1: Clean dataset (by removing inoperable runway images) with a **Binary Classification Task**
  - creation of a dataset where the piano is **fully visible, centered** in the frame, and **aligned** with the runway direction (facing "up"). ➔ 12 000 images
  - Fine-tune a Vision Transformer (ViT) model
  - **Training Data**: ~3,400 **manually labeled** images
    - 2,300 valid, 1,200 invalid
    - Data split: 70% train, 20% test, 10% validation.
  - **Final Cleaned Dataset:** 8,000 valid runway images

Calibration procedure – step 2

- Step 2: Corner database correction
  - **Step 2.a YOLO model** to detect the bounding boxes of the piano (again partial manual labeling, training …)
  - Step 2.b: Given
    - Pixel coordinates of the lower corners of the piano
    - Latitude/longitude coordinates of the piano center
    - The configuration of the image generator

    ➔ Computation of **latitude and longitude** of the piano’s lower corners



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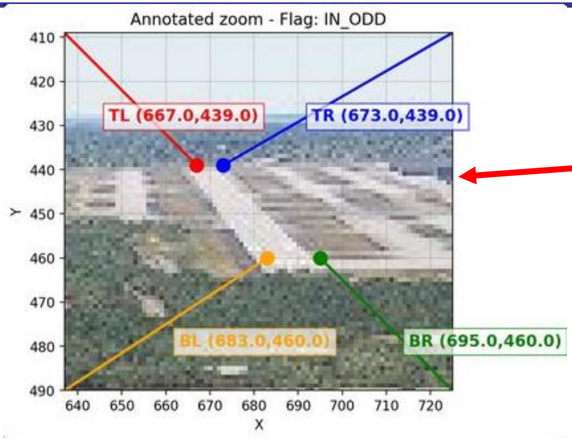
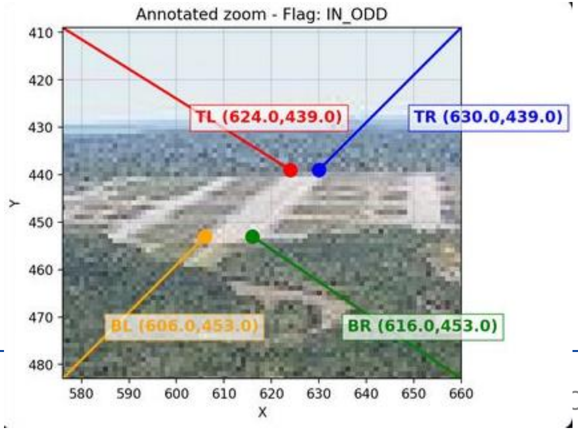
Data set description

- 30 images per runway:
  - 10 images at random positions / orientations within ODD
- Total number of runways ~ 980
  - Expected ~30,000 images per generator
- Final (after cleaning): 115,259 images

Generator	GES	FlightSim	Xplane	ArcGis	Bing
Nb images	22,762	26,959	25,550	21,863	18,125
Time	15h	40h	15h	15h	15h

Labelling – multiple runways



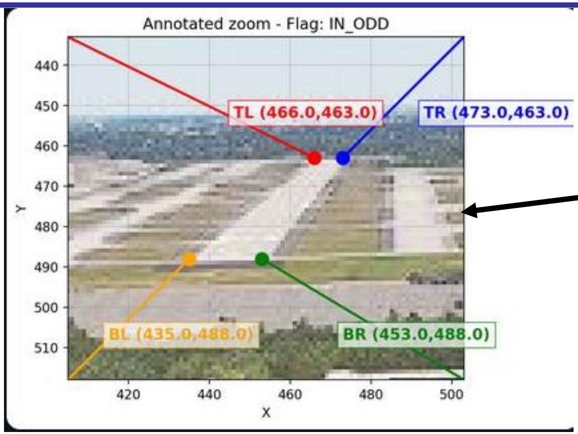


airport: KATL (Hartsfield–Jackson Atlanta International Airport); runway: 27R

pose:

- -84.37375290725308
- 33.633524048700345
- 438.0442097414649
- -99.09592664669934
- 84.4536867156202б
- 1.2912211981490436

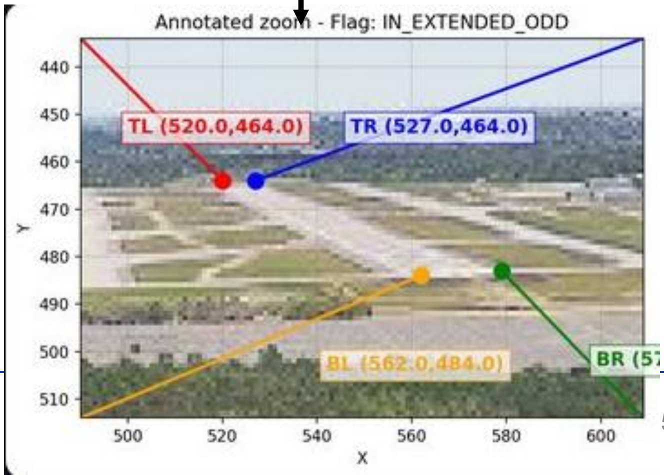
Labelling – multiple runways



airport: KATL (Hartsfield–Jackson Atlanta International Airport); runway: 9L

pose:

- -84.47207814339873
- 33.63372456371015
- 418.1794154938892
- 91.5573759286276
- 85.6118838827599
- 1.5430039651336043



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Provided with LARD V2

- Models:
  - YOLO family models (e.g., YOLOv5, YOLOv8)
  - DeTR (DEtection TRansformer)
  - FCOS (Fully Convolutional One-Stage Object Detection)
- Metrics:
  - Extended mAP (to take into account inODD, extendedODD…)

Benchmark of trained model with LARD V2

Training of a YoLo v8

- On all airports and all sources

Test on a real footage

- YouTube channel GreatFlyer @greatflyer_aviation
- Video of a landing into sunny Lanzarote in the Canary Islands https://youtu.be/Z6A5dsk2wjc
- Lanzarote not in the LARD V2 airport list
- Camera in the cockpit

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Conclusion

- Improved open-source runway image dataset
- Data available at Hugging face
  https://huggingface.co/datasets/DEEL-AI/LARD_V2

- Open to external contributions
  – Improve script to attack data generator
  – ML models, ML metrics